Analysis of the Los Angeles Metropolitan Office Market

by

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Bachelor of Law
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Submitted to the Department of Urban Studies and Planning
in Partial Fulfillment of the Requirements for the Degree of

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Abstract

The thesis predicts the future of the Los Angeles metropolitan office market through analysis of the office decentralization in the area, particularly facts and causes. We first look at the real estate data for 43 submarkets in the metro area Through studies of the area's office market, the long term trend of the decentralization was observed. As Los Angeles County declined in share of employment and office stock, other regions grew continuously over the years.

As causes of the decentralization, we focus on wage differentials and commuting time of each subcenter. Estimated wage premia and average commuting time are found to vary significantly over the subcenters. Also positive and significant correlation is found between wages and commuting time, as urban economic theory predicted. Therefore, there is an incentive for firms to move out to the locations with shorter commuting time.

Comparing real estate data directly to average commuting time and estimated wage premia, we estimate relationships between facts and causes. Two equations are adapted to this estimate for scale and growth of subcenters. As a result, larger subcenters are found to have longer commuting time and higher wage premia; shorter commuting time and lower wage premia cause faster growth of subcenters. Thus, smaller subcenters with shorter commuting time and lower wage premia are proved to have a potential for future growth.

Finally, we forecast future vacancy rates and rents of each subcenter. Most of the badly performing subcenters are located in Los Angeles County, whereas the well performing subcenters are located in peripheral counties. In addition, the total score calculated for each subcenter tells us that the central locations will decline further in future, whereas subcenters at the fringe locations will grow. Therefore, we concluded there is less hope for office markets in the central locations.

Thesis Supervisor: William C. Wheaton
Title: Professor of Economics and Urban Studies and Planning

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My advisor, Professor William C. Wheaton, who had provide me with precious advise and idea throughout the thesis writing process and also accepted me to use the data from his research company.

Mr. Darren Timothy, a doctor student of the Department of Economics, who originally developed the approach of estimating wage premia, which we used in this thesis, and instructed his methodology very kindly to me.

Mr. John A. Southard and Ms. Laura Stone from CB Commercial/Torto Wheaton Research, who helped estimation from the data and also gave me a lot of advises.

Without these people, this paper could not have been completed. Thank you.

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1. Introduction and Thesis Outline

1.1. Introduction

Over the past decade the decentralization of office firms from major metropolitan areas in the US has been a common phenomenon. While many American cities still contain large central business districts with numerous high-rise office buildings, office construction activities outside of the central business districts (CBDs) have increased dramatically since 1988. For example, Boston's share of regional jobs in finance, insurance and real estate (FIRE), and service sectors dropped 12 percentage points from 47% to 37%, while shares of numerous suburban communities rose (DiPasquale & Wheaton 1995).

This current of decentralization caused the CBD market's decline and the suburban location's rise to prosperity in most metropolitan areas. Moreover, the recent property recession spurred this downward trend of the CBD office markets. Office buildings with huge vacant space left are familiar scenes in the central locations nowadays. There seems to be no more bright future in the CBDs, whose skyscrapers once were symbols of American prosperity, but now are becoming real white elephants. Is this really true? Is there really no hope for the CBD office markets?

The object of this thesis is to predict the future of the Los Angeles office market, through analysis of the decentralization in the Los Angeles metropolitan area, particularly facts and causes. Through a study of the office market history, facts of decentralization in the area are first observed. We next examine wages and travel time of workers in various locations of the area. Urban economic theory concluded that wage differentials over subcenters result in decentralization of office locations, and wages are related to travel time in the same location. Thus, estimations of relationships between wages and travel time tell us the trend of decentralization in the area. Finally, by forecasting future office markets, we not only answer the question, but also suggest what the US metropolitan areas will be like in the future.

1.2. Thesis Outline

The thesis is organized as follows.

Chapter 2 analyzes the history of the Los Angeles metropolitan office market, using the CB Commercial data for 43 submarkets in the area. We explain each county's office market as well as the whole metropolitan area. The long term trends of the area clearly suggest decentralization of its employment and office stock, although the downtown market still keeps stable share of area's office absorption. Prior to 1987 the area was characterized by widely differing vacancy rates. But more recently vacancy rates have converged to more equivalent rates.

Chapter 3 focuses on causes of decentralization, particularly travel time of workers and wage differentials. The approach developed by Darren Timothy is employed. Using the microdata from the 1980 Census and the 1990 Census, average travel time and wage premia of each work location are calculated. The results show travel time and wage premia vary significantly across work locations of the metropolitan area. Also, there are significant positive correlation between travel time and wage premia.

Chapter 4 estimates relationships between facts and causes of decentralization. Real estate data from the CB Commercial are directly compared with average travel time and estimated wage premia from Chapter 3. Two equations are adapted in order to estimate these relationships in terms of scale and growth of subcenters. The results support urban economic theory; larger subcenters have longer travel time and higher wage premia, and shorter travel time and smaller wage premia cause faster growth of subcenters.

Chapter 5 forecasts vacancy rate and rents of each subcenter in the metropolitan area during 6 years from 1995 to 2000, using equations estimated in Chapter 4. Los Angeles

County shows the worst performance in terms of both forecasted vacancy rates and forecasted rents. On the other hand, two of the best performers in terms of vacancy rate is located at Orange County and all of the best performers in terns of future rents are located at either Riverside County or San Bernardino County.

Finally, Chapter 6 concludes the thesis with a summary of the results and findings. The best subcenter and the worst subcenter for investments are presented.

Finally, Chapter 6 concluded the thesis with a summary of the results and findings. The best and the worst subcenters are presented.

2. History of the Los Angeles Office Market

2.1. The Los Angeles Metropolitan Area

2.1.1. Overview

The Los Angeles metropolitan area is ranked as the second largest metropolitan area in the United States, with a population of 14.5 million people[1] (Bureau of Census 1994). The metropolitan consists of five counties: Los Angeles County, Orange County, Ventura County, Riverside County and San Bernardino County, these counties have a total office employment of 1,123 million people and 238 million square feet of office stock. In the past, the area's unemployment rate was quoted at 10.3% in the third quarter of 1994, significantly higher than the national unemployment figure of 6.1% (Cushman & Wakefield 1994). Recent quakes, riots and floods plunged the area's fiscal management into harsh conditions. Los Angeles County is suffering from a 1.2 billion dollar budget gap and considering a plan to slash more than 18,000 jobs, 20% of the country work-force (Schine 1995). In the early 1995, Orange County filed for bankruptcy because of failure in speculative investments. These fiscal problems in the area raise speculations of increasing property tax in near future.

After the property crash of the early 1990s, the office property market in the metropolitan area plunged into recession. In 1991, the area recorded the highest vacancy rate of 21.3%, according to CB Commercial data; this rate is approximately 4% higher than the average of previous five years. Thereafter, the rate has gradually decreased up to 19.5% in 1994, which is slightly smaller than 19.7% in 1993.

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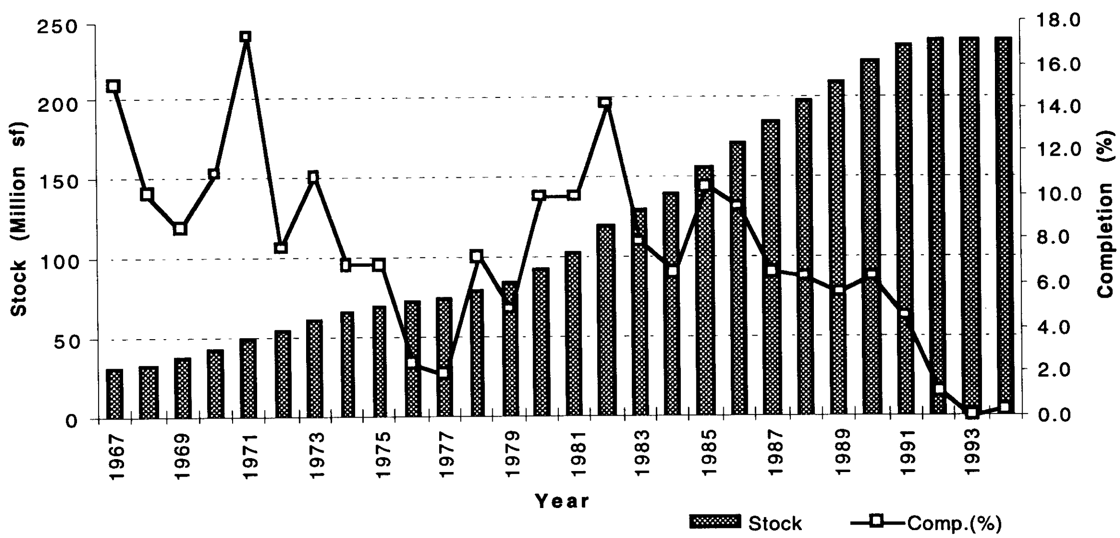
[1] This number is sum of population in Los Angeles County, Orange County and Riverside County.

Figure 2.1 compares office stock and the annual completion of space as a percentage of stock in the area. Completion of new office space is not always linked to the U. S. macro-economy. Completion dropped sharply just after the recession of 1975 and 1990, but continued to rise through the downturns in the early 1980s. This unique outcome in the early 1980s can be explained by the policy implemented by the Reagan administration. Deregulation of financial institutions had created excess funds available for new investments and the 1981 tax reform had fueled investments in the property market. Figure 2.1 also shows that, in the Los Angeles metropolitan area, the building boom in the 1980s was much smaller than the earlier boom from the late 1960s to early 1970s when measured as a percentage of the existing stock. This implies that the area's office market has matured through the early 1980s; a rapid growth in this area would not be expected thereafter.

Figure 2.1: Total Stock & Completion as a Percentage of Stock in the LA Metropolitan Area



Source: CB Commercial/Torto Wheaton Research

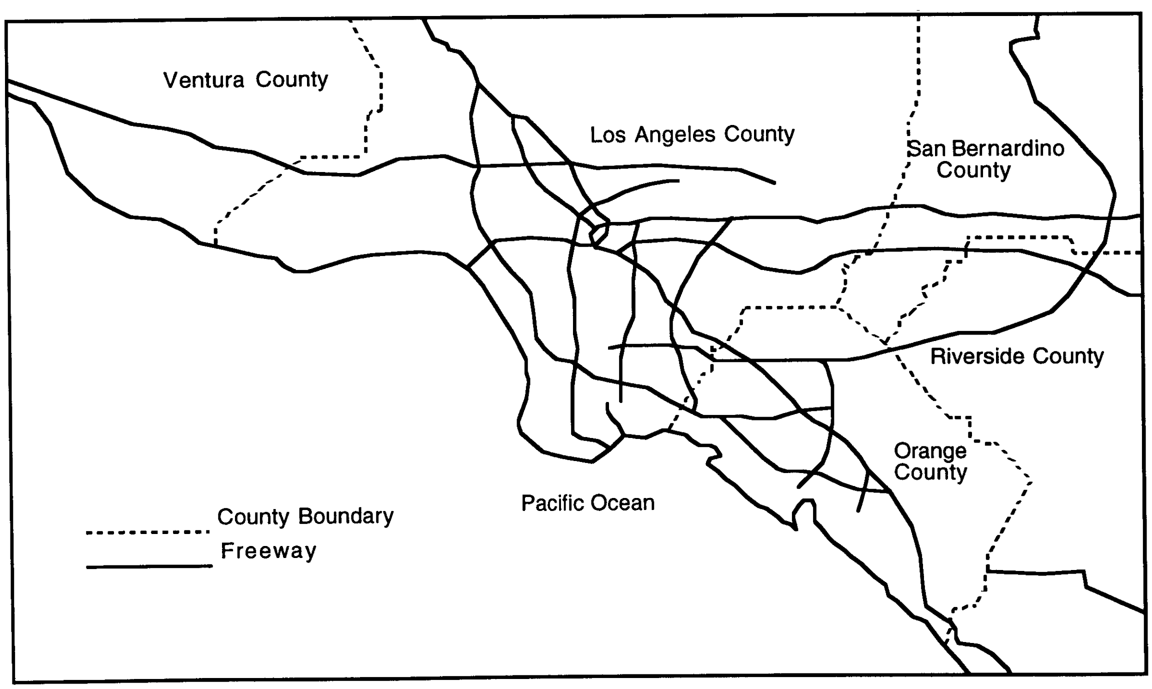
2.1.2. Area Definition

"Los Angeles" has three different conceptual meanings:

1) The Los Angeles metropolitan area[2]
2) Los Angeles County
3) Los Angeles City

The Los Angeles metropolitan area is shown in Figure 2.2. In this paper, the Los Angeles metropolitan area is used for identifying the Los Angeles office market. This metropolitan area consists of four large regions: Los Angeles County, Orange County, Oxnard (Ventura County), and Riverside County/San Bernardino County, according to the

Figure 2.2: Los Angeles Metropolitan Area



[2] In real estate terms, the greater Los Angeles includes four metropolitan statistical areas (MSAs) in Southern California: the Anaheim-Santa Ana MSA, the Los Angeles-Long Beach MSA, the Oxnard-Ventura MSA and the Riverside-San Bernardino MSA (Crubb & Ellis. 1993).

CB Commercial data. Giuliano & Small (1991) distinguished 32 employment subcenters in the metropolitan area, adapting their empirical criteria for identification. We, however, define this metropolitan area with 43 office submarkets, as shown in Table 2.1, using the data from a real estate brokerage firm, CB Commercial. Since the purpose of this chapter is to analyze the office market, the firm's definition of the area could be more suitable for this purpose[3].

Table 2.1: Office Submarkets & Changes in Their Shares of Stock

SUBMARKETS	STOCK (1000sf)			
Los Angeles Co	**1974**	**Share**	**1994**	**Share**
Beverly Hills	2277	3.4%	3483	1.5%
Beverly Hills Triangle	1785	2.7%	2574	1.1%
Brentwood Corridor	440	0.7%	3294	**1.4%**
Burbank/N. Hollywood	328	0.5%	6116	**2.6%**
Century City	3930	6.0%	8507	3.6%
Cerritos	779	1.2%	3611	**1.5%**
Covina/Pomona	206	0.3%	2971	**1.2%**
East Los Angeles	0	0.0%	936	**0.4%**
El Monte/Baladwin Pk	682	1.0%	3690	**1.5%**
Fox Hills	39	0.1%	2534	**1.1%**
Hollywood	2330	3.5%	2646	1.1%
LA Downtown	15802	23.9%	35862	15.0%
LA Suburban	273	0.4%	525	0.2%
LAX/El Segundo	2546	3.9%	11021	**4.6%**
La Puente/Vlly Blvd.	0	0.0%	1491	**0.6%**
Long Beach	1614	2.4%	7738	**3.2%**
Marina Del Rey	711	1.1%	1195	0.5%
Mid-Wilshire	7919	12.0%	9033	3.8%
Miracle Mile	2830	4.3%	4590	1.9%
N San Fernando Vlly	88	0.1%	1904	**0.8%**
Olympic Corridor	60	0.1%	1796	**0.8%**
Park Mile	828	1.3%	1293	0.5%
Pasadena/Glendale	3318	5.0%	13698	**5.7%**
Santa Monica	503	0.8%	6281	**2.6%**
Sherman Oaks/Vn Nuys	2373	3.6%	8351	3.5%
Thous Oaks/W'lake Vg	491	0.7%	1340	0.6%

SUBMARKETS	STOCK (1000sf)			
	1974	**Share**	**1994**	**Share**
Torrance/Carson	388	0.6%	6893	**2.9%**
Warner Ctr/W Vlly	1251	1.9%	9078	**3.8%**
West Hollywood	912	1.4%	1121	0.5%
West Los Angeles	190	0.3%	3032	**1.3%**
Westwood	1801	2.7%	3168	1.3%
Total	56694	85.8%	169772	71.2%
Orange Co				
Coastal/ Airport	2699	4.1%	25581	**10.7%**
Ctrl Orange Co	3382	5.1%	12469	**5.2%**
North Orange Co	540	0.8%	4099	**1.7%**
South Orange Co	181	0.3%	4247	**1.8%**
West Orange Co	180	0.3%	3022	**1.3%**
Total	6982	10.6%	49418	**20.7%**
Oxnard				
Camarillo	75	0.1%	686	**0.3%**
Conejo Valley	193	0.3%	2504	**1.1%**
Oxnard/Pt Hueneme	267	0.4%	1015	**0.4%**
Ventura County	518	0.8%	1827	0.8%
Total	1053	1.6%	6032	**2.5%**
Riverside/San Bernardino Co				
East Valley	441	0.7%	3708	**1.6%**
Pomona Valley	45	0.1%	4084	**1.7%**
Riverside	831	1.3%	5300	**2.2%**
Total	1317	2.0%	13092	**5.5%**
LA Metro Area Total	66046	100%	238314	100%

Source: CB Commercial/Torto Wheaton Research

[3] The Los Angeles metropolitan area is defined with 28 work locations in the Public Use Microdata. We use this area definition to estimate wage differentials and average travel time in the Chapter 3. In the Chapter 4, we merge 43 office submarkets into 28 in order to fit the Census definition.

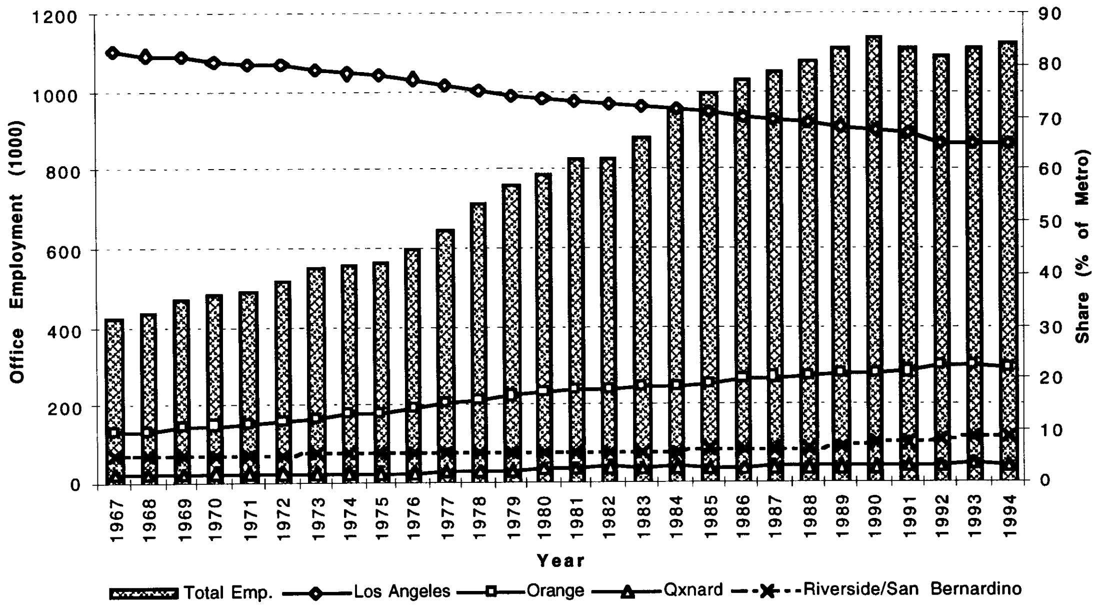
2.1.3. Long Term Trends of Subcenters' Office Stock

Total office stock of the area is approximately 238 million square feet in 1994 according to the CB Commercial data. Table 2.1 also shows office stock of each submarket and its share of the metropolitan area both in 1974 and 1994. Bold indicates growth of share in 1994 compared to the share in 1974. Los Angeles County alone decreased its share in the metropolitan area; 13 of its 30 submarkets lost their share since 1974. Particularly the center markets, the downtown and Mid-Wilshire Corridor, declined significantly. In contrast, most of submarkets in the other three regions raised their presence in the area, with an exception of West Orange County.

2.2. Long Term Trends in Office Employment

Decentralization can also be seen by examining the government produced employment data. Figure 2.3 presents changes in total office employment in the metropolitan area and percentage share of each county of the area during 28 years. Total office employment in the metropolitan area peaked in 1990 at the level of 1,145 thousand office workers. This number had grown rapidly and consistently without a major slump from 424 thousand in 1967; the average annual growth rate of these 28 years was approximately 4.7%. However, the total figure has hit a plateau these past four years and never come back to the level in 1990.

Figure 2.3: Total Office Employment in the LA Metropolitan Area & Share of Each Region



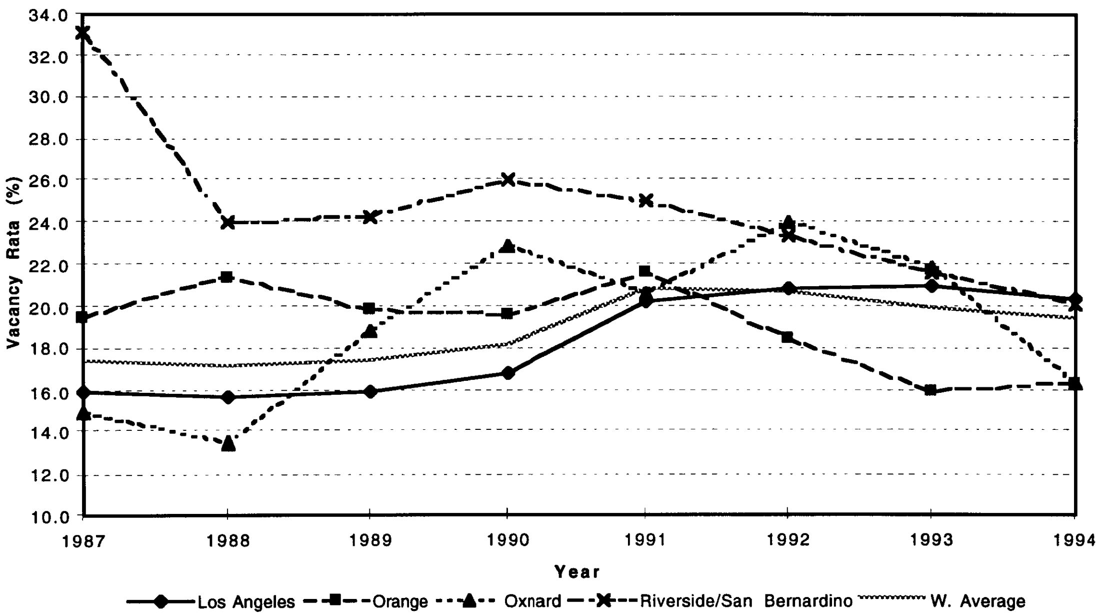
Source: CB Commercial/Torto Wheaton Research

It is also clear from Figure 2.3 that decentralization has been a long term trend in the metropolitan area from the early stage. Los Angeles decreased its share in the area's office employment to 65.3% in 1994 from 82.9% in 1967. On the other hand, although the other three regions gained their shares together in this period, Orange County has grown most rapidly by 12.4 points in its share from 9.8% to 22.2%; its average annual growth rate in these 28 years was approximately 8%.

2.3. Recent Trends of the Office Markets

The weighted average vacancy rate in the area has been stable within the range from 17 to 21% since 1987, as shown in Figure 2.4. In the three markets, Los Angeles County, Orange County and Oxnard, vacancy rates have moved closely together since 1987. Riverside County/San Bernardino County, on the other hand, has consistently shown

Figure2.4: Average Vacancy Rate of Each Region



Source: CB Commercial/Torto Wheaton Research

higher rate than each of the other three markets until 1992, particularly 15.7% higher than the weighted average rate in 1987. Currently, however, data shows that all four markets are in the smallest range of 4% in 1994. This may suggest that the Riverside County/San Bernardino County office market had been independent from the metropolitan market until 1992, but has joined since then.

Figure 2.5[4] represents each county's share of net absorption in the area's office market. In 1994, Orange County was a big looser with negative net absorption, whereas the other three regions increased their shares, particularly Oxnard, whose share increased to 29.0% from 4.2%. The Oxnard market, only 2.5% of the area's stock, absorbed a

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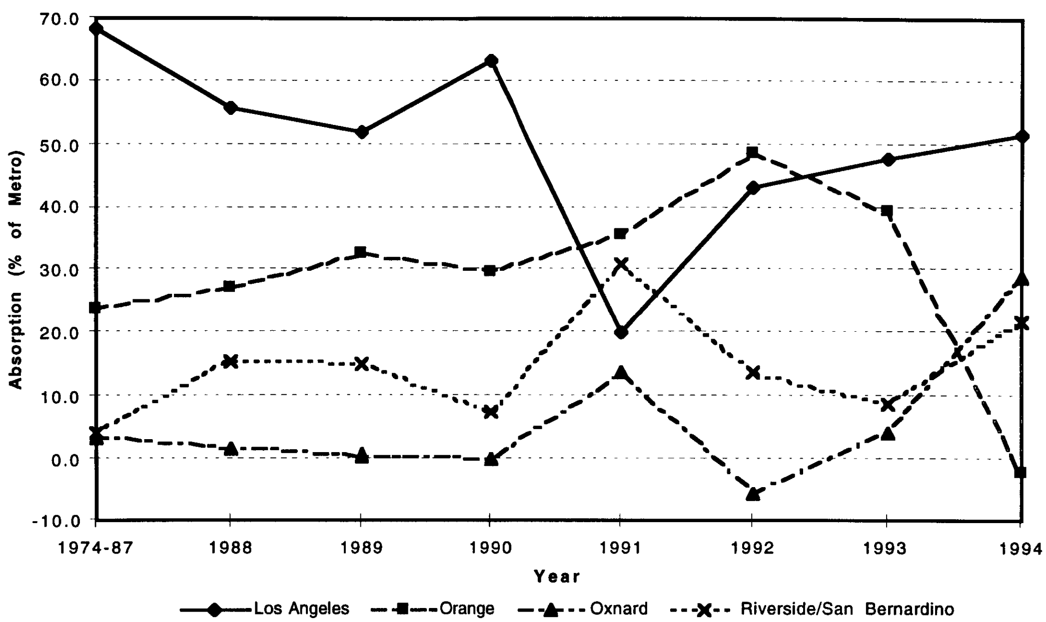
[4] In the data from CB Commercial, vacancy rate of each market is available only from 1987. In order to calculate the average absorption between 1974 and 1987, we first assumed the vacancy rate of the Los Angeles in 1974, 15.3%, as each submarket's vacancy rate in 1974, since vacancy rate in Los Angeles County is available even during 1974 and 1987. Then, we calculated the average absorption in 13 years from 1974 to 1987 by following equation:

(stock in 1987 x vacancy rate in 1987 - stock in 1974 x 15.3%) / 13 years

This calculation was used for all average numbers during 1974 and 1987 in following graphs of this chapter.

significant amount of space in 1994. Similarly, in the early 1990s, Los Angeles County lost its share of absorption by more than 40 points from the over 60% level in 1990.

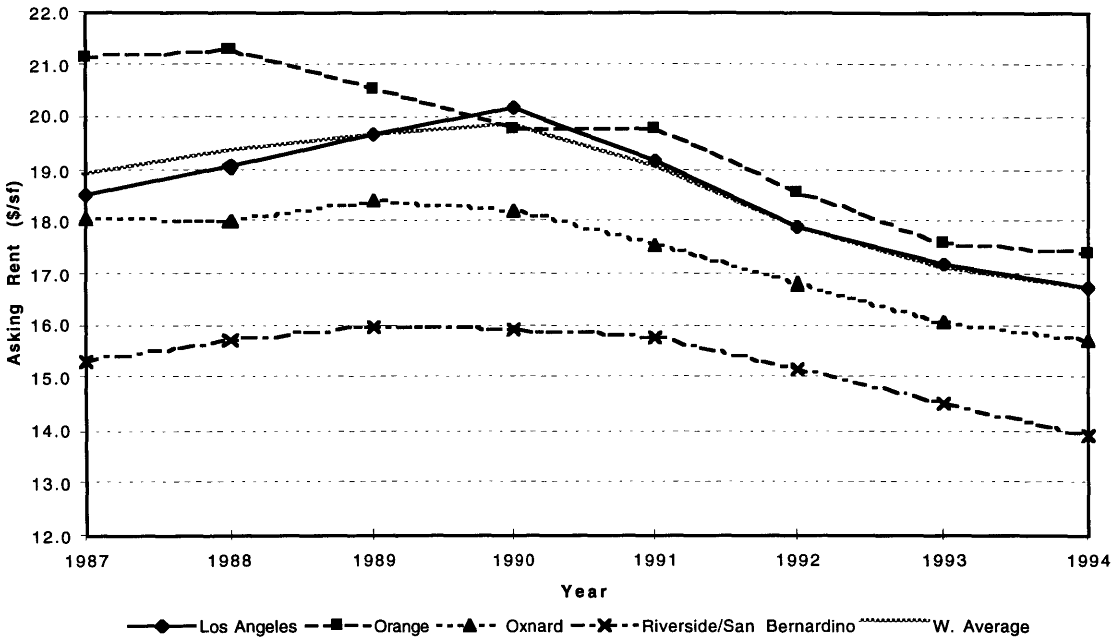
Figure2.5: Each Region's Share in Net Absorption



Source: CB Commercial/Torto Wheaton Research

Over the long term, Los Angeles County has lost its share of absorption; it had only 50% share in 1994, although once it had dominated the metropolitan market with an average share of 70% during the period from 1974 to 1987. The other three regions (Orange, Oxnard and Riverside/San Bernardino) have grown their market. Particularly, the two peripheral regions, Oxnard and Riverside County/San Bernardino County, have increased their share enormously up to 29% and 22% respectively in 1994, from their average shares between 1974 and 1987, 4.3% and 3.5%. Orange County also has grown its share rapidly above the 40% level in recent years, which was nearly doubled from the average share of 24% in the previous 8 years, although the county experienced a strong downward movement in 1994. As a result, the difference of shares among the four regions has been diminished in terms of net absorption.

Figure 2.6: Average Asking Rent of Each Region



Source: CB Commercial/Torto Wheaton Research

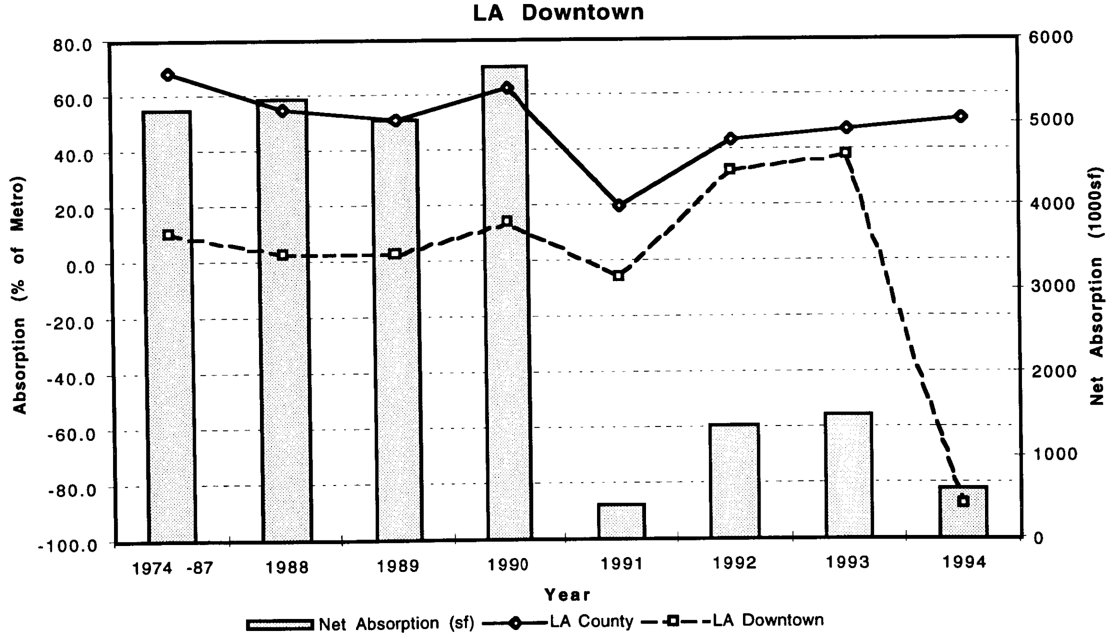
Average asking rents in the four markets have decreased continuously and constantly since 1991 by approximately $1 per square foot per year. In addition, those markets have been very well correlated with each other since then. The difference between the highest rent, Orange County, and the lowest, Riverside County/San Bernardino County, is $3.5 per square foot in 1994 (Figure 2.6). This dollar difference is clearly smaller than that in 1987, which was $5.8 per square foot. Therefore, we could say there was a convergence in the office rent level in the area's market in the early 1990s. Thereafter, rents have stabilized in all four regions.

2.4. Regional Markets

2.4.1. Los Angeles County

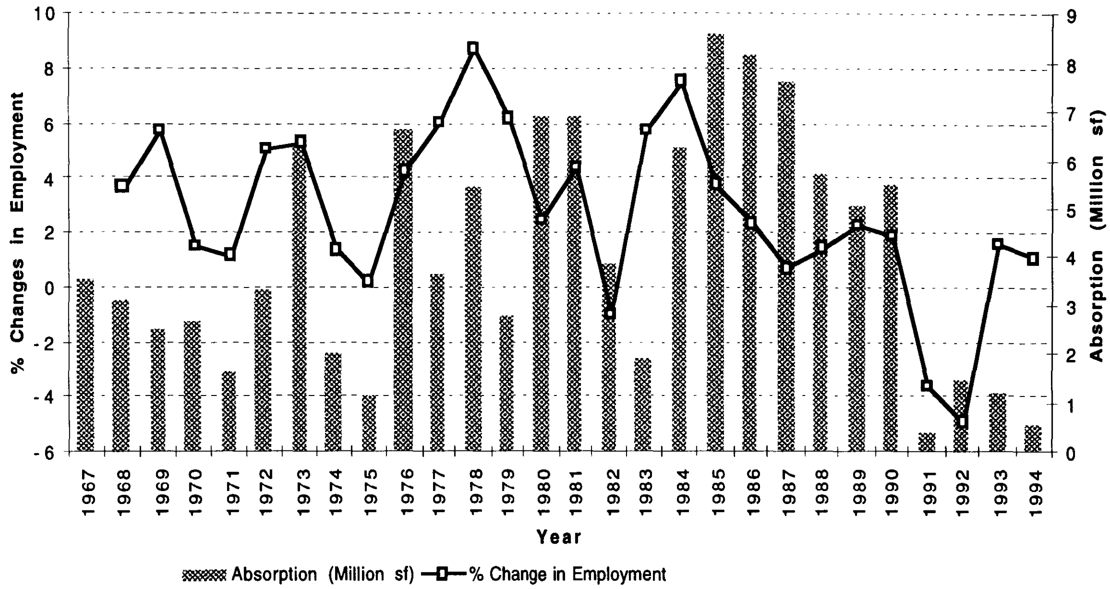
Los Angeles County contains the greatest number of office submarkets in the entire metropolitan area, with 71.2% of the area's total office stock. Downtown LA alone comprised 15% in 1994. Over the long term, the county has diminished its presence. Figure 2.7 shows that its share of net absorption in the metropolitan area decreased to the 50% level in 1994 from the average between 1974 to 1987, 68.4%. The downtown market, however, has kept its share stable, with an exception of extreme large negative absorption in 1994. As a result, other submarkets in the county declined in share of absorption particularly during the past several years.

Figure 2.7: Net Absorption in LA County & Shares of LA County and LA Downtown



Source: CB Commercial/Torto Wheaton Research

Figure 2.8: Office Employment and Absorption in LA County



Source: CB Commercial/Torto Wheaton Research

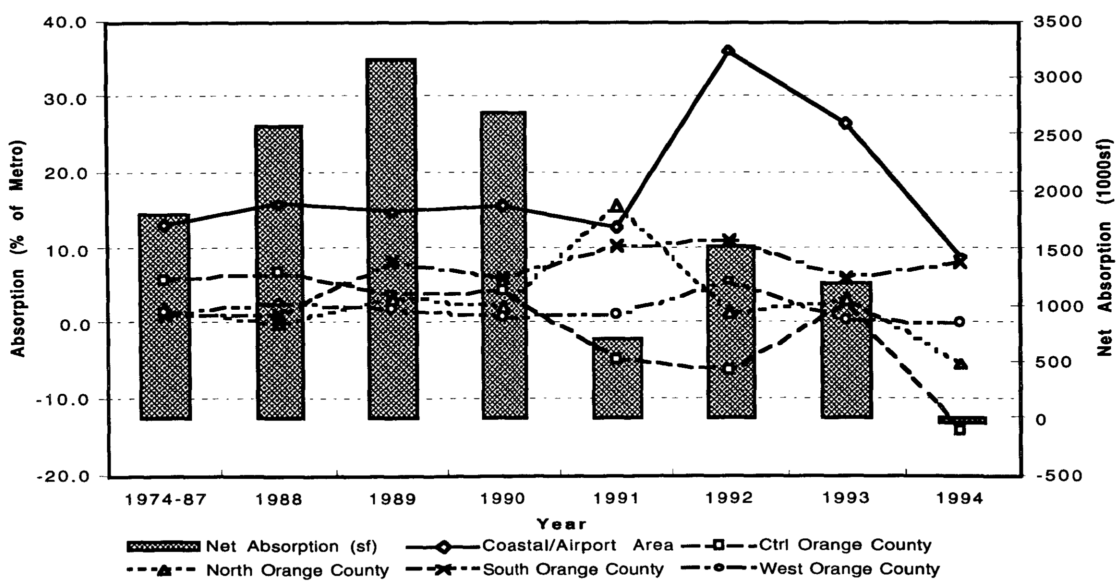
Figure 2.8 compares annual office employment growth with the annual net absorption of office space in Los Angeles County. It is observed that office employment in Los Angeles County has reacted sensitively to the national economy, experiencing significant downturns near the national recessions in 1971, 1975, 1982, and 1992. Figure 2.8 also suggests that net absorption in Los Angeles County is significantly correlated with its office employment growth. The changes in office employment during the 1970s and 1980s were relatively constant, however, the county's net absorption during the 1980s was much larger than that in the 1970s. One explanation is that the total employment in the 1980s was greater than the 1970s. Another possible explanation for this is that during the 1980s each employee used more space than during the 1970s.

2.4.2. Orange County

Figure 2.9 shows total net absorption and each submarket's share of the metro area's net absorption in Orange County. As a long term trend, Coastal/Airport Area, the biggest submarket in the region, has grown farther with higher share of net absorption in the area particularly in 1992 and 1993, 36.2% and 26.5% accordingly. In contrast, Central Orange County, which once had the second highest average share of net absorption in the period from 1974 to 1987 has declined, experiencing negative net absorption in 1991, 1992 and 1994. The other three submarkets have grown gradually with a few exceptions for each submarket, especially in 1994.

Recently, particularly after the property crash in the early 1990s, vacancy rates in the region have converged at the lower level with an exception of Central Orange County, as show in Figure 2.10. The difference between the highest vacancy rate and the lowest in the region dropped to 4.4 points in 1992 from the largest level of 20.6 points in 1988, as

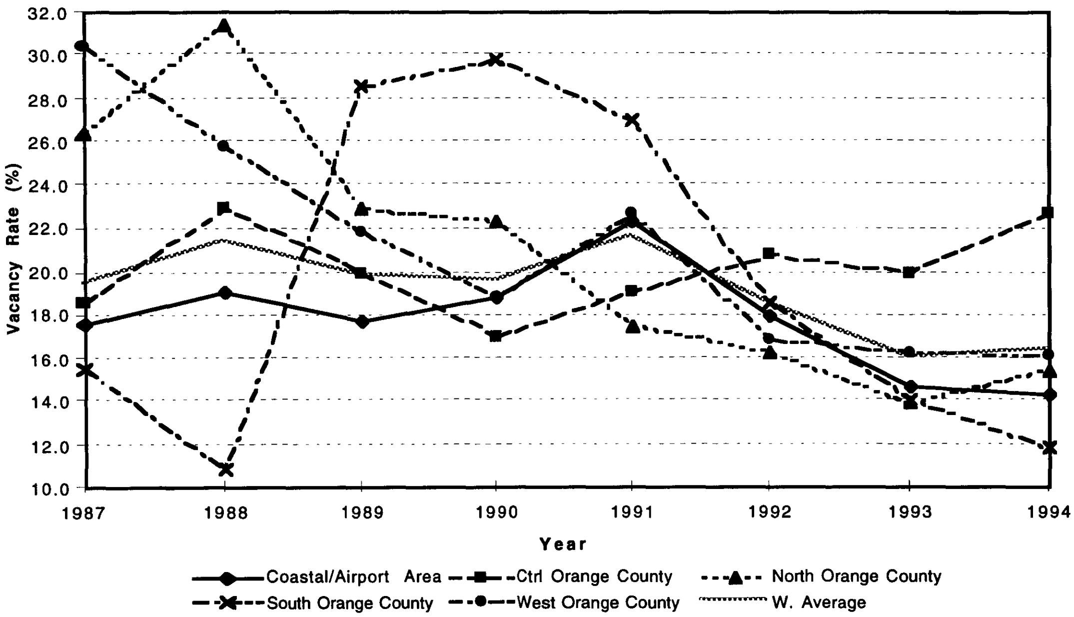
Figure 2.9: Net Absorption & Each Submarket's Share in Orange County



Source: CB Commercial/Torto Wheaton Research

the average vacancy rate in the region decreased. This lowering vacancy rate and convergence of the vacancy rates in the region are mainly due to the limited amount of new supply coming into the market. The submarkets in the region had new completion of only 216,000 square feet in the past three years.

Figure 2.10: Vacancy Rate of Each Submarket in Orange County

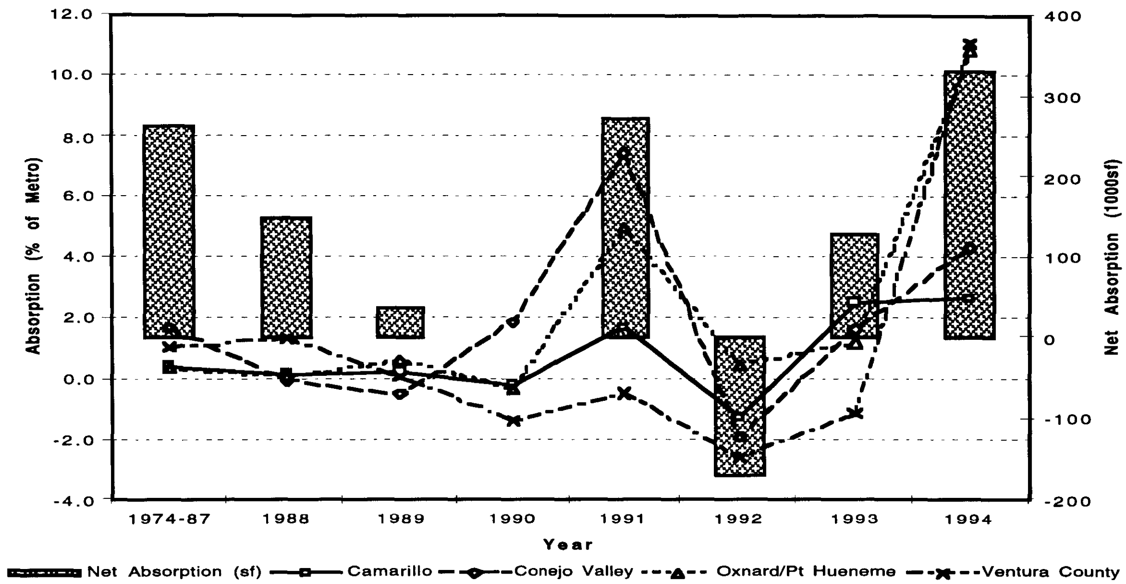


Source: CB Commercial/Torto Wheaton Research

2.4.3. Oxnard

The Oxnard office market appeared to be extremely volatile in Figure 2.11, with a considerably small stock of 6 million square feet, showing the lowest net absorption of -170,000 square feet in 1992, and the highest of 333,000 square feet in 1994. Consequently, submarkets in the region show unsteady movements, largely due to their limited size of office stock. Over the long term, however, most submarkets in the region have increased their shares of net absorption in the metropolitan area. For example, these four submarkets had the average shares of only 0.4 to 1.7% in the period from 1974 to

Figure2.11: Net Absorption & Each Submarket's Share in Oxnard

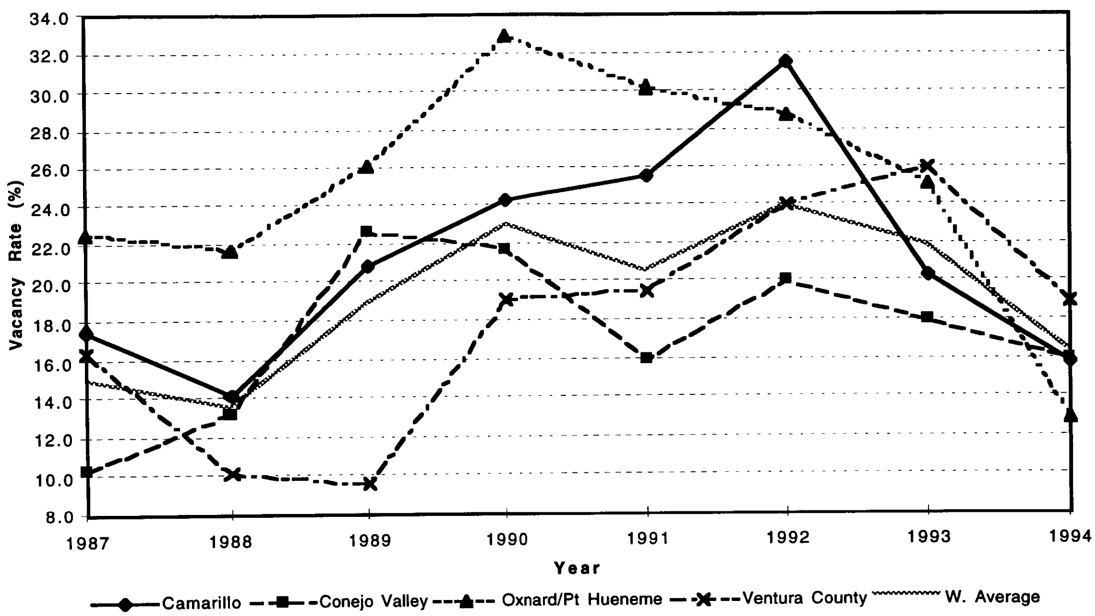


Source: CB Commercial/Torto Wheaton Research

1987, but in 1994 Oxnard/Port Hueneme and Ventura County recorded over 10% shares of absorption.

Similar to the changes in shares of net absorption, vacancy rates of the region's submarkets moved widely. Camarillo with only 600,000 square foot stock, for example, varied its vacancy rate from the lowest, 14.2% in 1988, to the highest, 31.5% in 1991, as shown in Figure 2.12. Similarly Oxnard/ Port Hueneme had 1,015,000 square foot stock, whose vacancy rates ranged from the highest of 32.9% in 1992 to the lowest of 12.9% in 1994. However, although each market in the region has been volatile, the region as a whole has been smoothed since 1991. In 1990, for example, there was 13.8% difference between the highest vacancy rate and the lowest in the region. In contrast, in 1994, this difference was only 6.1%.

Figure 2.12: Vacancy Rate of Each Submarket in Oxnard

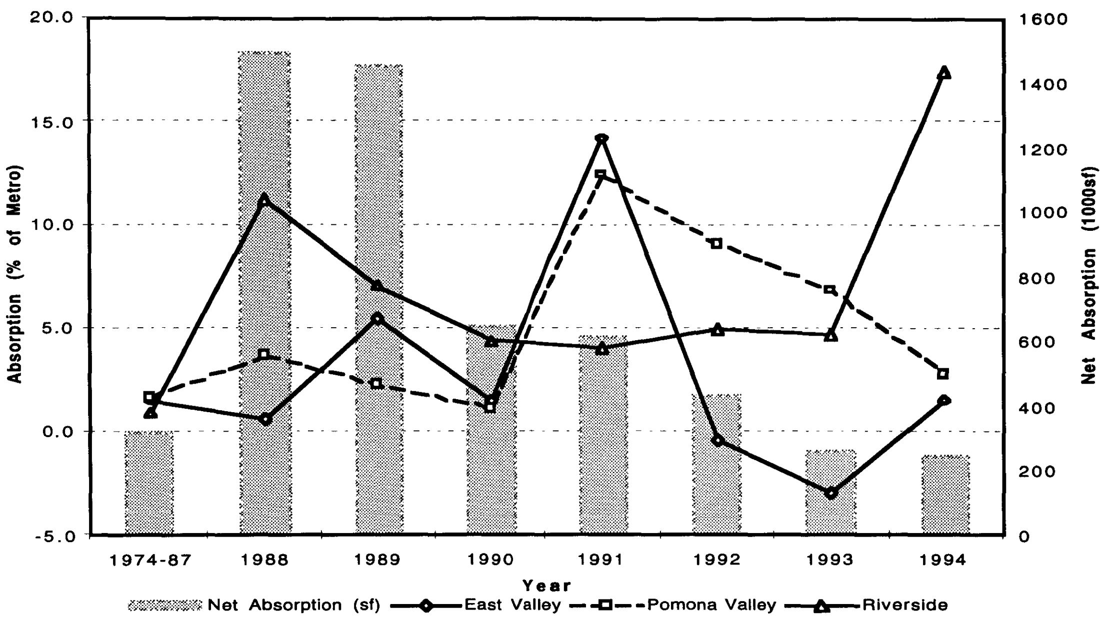


Source: CB Commercial/Torto Wheaton Research

2.4.4. Riverside County/San Bernardino County

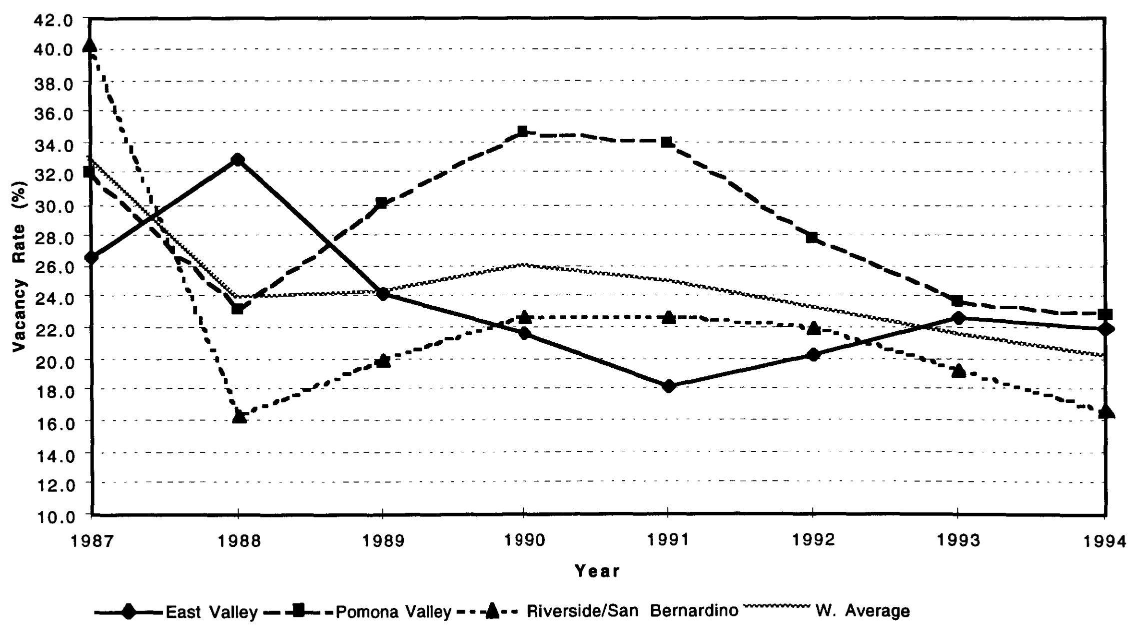
Riverside County/San Bernardino County is a rather new market and has existing office stock of 13 million square feet, representing 5.5% of the area's stock. This region had over 1.5 million square foot net absorption in 1988 and 1989, which is more than three times bigger than the average net absorption between 1974 and 1987 (Figure 2.13). Submarkets in the region also have a long term trend of increasing their shares of net absorption in the metropolitan area. Over the period from 1974 to 1987, the existed three submarkets had average shares of only 1.0 to 1.6%. However, most submarkets recorded higher shares in the past seven years, except in 1992 and 1993. As a short term trend, Riverside has grown rapidly, particularly in 1994, gaining a 17.4% share. In contrast, East Valley declined with negative absorption in 1992 and 1993.

Figure 2.13: Net Absorption & Each Submarket's Share in Riverside County/San Bernardino County



Source: CB Commercial/Torto Wheaton Research

Figure 2.14: Vacancy Rate of Each Submarket in Riverside County/San Bernardino County



Source: CB Commercial / Torto Wheaton Research

The region once suffered from extremely high vacancy rates, especially in 1987; Riverside experienced 40.3% vacancy rate in that year, as shown in Figure 2.14. After 1990, however, the average vacancy rate has decreased gradually to 20.4% in 1994, close to the area's average rate of 19.4%. All markets in this region are very well correlated to each other showing smoothed and stable movements, although Pomona Valley has experienced very high vacancy rate in 1990 and 1991 due to sudden reduction in the region's net absorption in those years. As in the other regions in the Los Angeles metropolitan area, Riverside County/San Bernardino County reduced the range of its submarket's vacancy rate in recent years.

2.5. Conclusion

As office employment of the Los Angeles metropolitan area grew over the years, Los Angeles County lost its share gradually. Consequently, submarkets in the county diminished their share of office absorption and office stock in the area, due to the rapid growth of suburban submarkets. According to the data, most submarkets in the other three regions showed increases over the long term. Therefore, decentralization is a long term trend of the office markets in the Los Angeles metropolitan area. However, it is worth mentioning that the downtown market maintains a stable share of absorption in the area, although it lost a significant share of total stock.

In the past several years, particularly after 1990, vacancy rates have converged into a small range in most of the regions, including the whole Los Angeles metropolitan area. This convergence is due to the constraint of new supply in the markets after the property crash in the early 1990s, in addition to the decentralization of office employment in the area. Also, differences in asking rent levels in the area have diminished in this period.

3. Travel Time and Estimation of Wage Differentials

3.1. Introduction

In Chapter 2, we observed a long term trend of the decentralization of office employment and office locations in the Los Angeles metropolitan area, through analysis of its office market history. In this chapter we focus on the causes of decentralization in the Los Angeles metropolitan area, particularly with respect to travel time of workers. We examine whether wage differentials between work zones result in differences in commuting times, as predicted by the urban economic theory. According to this model, a correlation between wage differentials and commuting time indicates an incentive for cost-minimizing firms to move to the locations closer to their workers.

In the 19th century, manufacturing firms tended to concentrate around the central locations surrounding a regional port or transportation facilities in order to ship and receive raw materials and their goods. Changes in production technology toward more land intensive production processes have attracted these firms to fringe locations where land is cheaper. In addition, increased reliance on truck transportation has necessitated access to interstate highway systems. This explains, in part, the suburbanization of US manufacturing firms.

On the other hand, 19th century, office firms had little reason to locate near regional port or transportation facilities, since they did not ship products or receive inputs. Labor was the dominant and almost exclusive factor used in production for office firms, and therefore, office firms tended to stay in locations where they were able to assemble their work force economically and efficiently. Thus, office firms first concentrated at the CBD where the transportation system for workers was well established.

The suburbanization of urban populations in the U.S. has gradually led many office firms to move out from the center to some locations nearer to the residences of their employees. In addition, recent improvements in telecommunication and innovation of computer related information technologies have reduced the agglomeration benefit for office firms located in the center. The most important benefits for firms to locating away from metropolitan centers is that suburbanized firms face lower wage expenses in suburban areas than that at the center. This is mainly due to the fact that commuting costs are lower to workers, and they are therefore willing to work for lower wages. We look at these relationships between wages and commuting time in this chapter.

3.2. Theory

When the location of firms is fixed to a single urban center, around which households locate in concentric rings, workers are compensated for commuting to that center through variation in housing rents (Alonso (1964), Mills (1972), Muth (1969)). The longer a worker commutes, the cheaper the housing rents are. The following equation represents a rent gradient for housing in the stylized one center town[5]:

$$R(d) = (r^a q + c) + k\,(b - d), \text{ or, } r\,(d) = r^a + k\,(b - d)/q$$

[5] It is assumed that the stylized town has the following features;

i) Employment is at a single center, to which households commute along a direct line from their residence.

ii) Households are identical, and the number of workers per household is fixed.

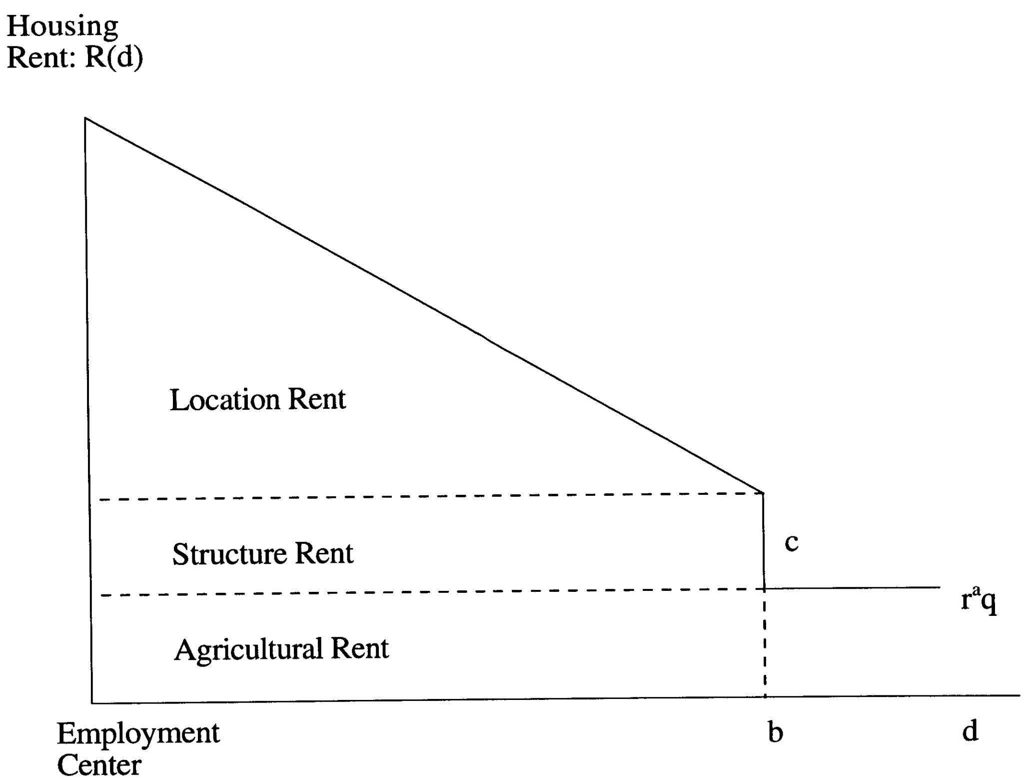
iii) Housing has fix and uniform characteristics at all locations.

iv) Housing is provided by combining a fixed amount of land per unit (q acre) together with a fixed amount of housing capital (c).

v) Housing is occupied by households who offer the highest rent, and land is allocated to that use yielding the greatest rent.

where R(d) is the housing rent per 1 unit, r (d) is the housing land rent per acre, r^a is the agricultural land rent per acre, c is the housing capital per 1 unit, k is the commuting cost per mile, b is the distance from the center to the city boundary, and d is the distance from the center. This equation implies that the shape of the rent gradient will be determined by the commuting cost function. In this town, rents exactly offset commuting cost and households would no longer have an incentive to move. Figure 3.1 explains this stylized one center town graphically.

Figure 3.1: Components of Housing Rent



Source: The Economics of Real Estate Markets (DiPasquale & Wheaton 1995)

Moses (1962), however, noted that wages varied among employment zones due to changes in the commuting cost. Firms moving to locations closer to the residences of their employees, he noted, could pay a lower wage rate to them— workers, employed in the

CBD and employed in the location near to their residence, should achieve the same utility level in equilibrium. Therefore, there should be an urban wage gradient in addition to a land rent gradient.

Figure 3.2 shows the spatial equilibrium model allowing an urban subcenter in addition to the CBD[6]. In this model, workers at the decentralized firm are paid lower wages than CBD workers since, on average, they have considerably shorter commuting distances. For example, at d_5, workers commuting leftward to the CBD or rightward to the decentralized firm would both pay the same for land, $r\ (d_5)$. On the other hand, those working at the decentralized firm have much shorter distances to commute than those working at the CBD. Therefore, the decentralized firm needs to pay only a wage w_2 which yields the same net income to its workers as the wage w_1 at the CBD:

$$w_2 - r\ (d_5) - k\ [d_2 - d_5] = w_1 - r\ (d_5) - k\ [d_5 - d_1],\ \text{ or, } w_2 = w_1 - k\ [d_2 - d_1]$$

This equation indicates a wage premium at the CBD, relative to the decentralized firm is proportional to commuting time differentials between both workers. If a firm locates further from the CBD, it will be able to pay increasingly lower wages.

The existence of such wage differentials provides a strong incentive for the cost minimizing firms to move out from congested employment centers to suburban location in order to decrease their wage expenses. However, no metropolitan area has reached complete decentralization. Instead, in most metropolitan areas, decentralized firms are clustered in subcenters. This phenomenon suggests that there is some agglomeration benefit for firms to concentrate up to a certain level. In a stable equilibrium, the decentralizing force and the agglomerating force must balance each other. Decreasing

[6] This model has following assumption:

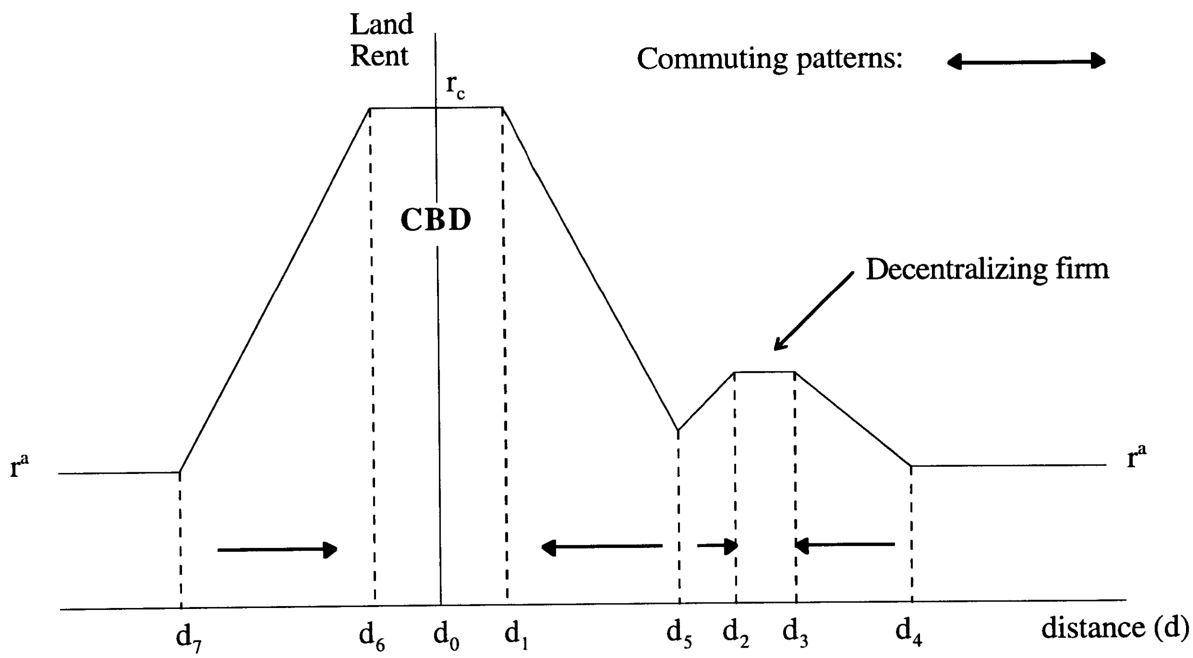
i) Within the CBD commuting cost is zero, so that workers must only pay to commute the edges of the CBD (d_1 or d_6).

ii) A firm could decentralize to an alternative location, using the land d_2 to d_3.

iii) All firms and workers are homogeneous.

agglomeration benefits due to changing environments (e.g., information technology) contribute to further decentralization.

Figure 3.2: Decentralizing Firms



Source: The Economics of Real Estate Markets (DiPasquale & Wheaton 1995)

3.3. Previous Researches

Moses (1962) attempted to supply a theoretical framework for the analysis of intraurban wage differentials and investigated some of its predictions about travel patterns. He hypothesized that there should be an intraurban wage gradient in addition to the rent gradient in order to explain intraurban variation in prices. He, however could not formulate a true spatial demand and supply analysis for labor in urban areas.

Madden (1985) used the data from the Panel Survey of Income Dynamics to test for systematic spatial variation in wages. She conducted an empirical study by focusing on changes in wages for individuals who changed job or residence during the previous year. Evidence of the existence of wage gradients was found, based on her finding that individuals changing jobs requiring more travel time from their homes, earned higher wages.

Ihlanfeldt (1992) used the 1980 Public Use Micro Data to estimate intraurban wage gradients for various groups of workers from the Philadelphia, Detroit, and Boston metropolitan areas. He estimated wage equations separately for groups of workers and categorized them by occupation, gender, race, and sector (private vs. public). As a result, negative and statistically significant wage gradients were found for most white workers. In contrast, positive wage gradients were not found for black workers.

McMillen and Singell (1992) produced a positive correlation between work and residence location and a negative wage gradient, using the 1980 Census data for the seven major northern metropolitan areas in the US. They first estimated reduced-form probit models for work and residence location choice and found support for their hypothesis that residence location significantly influences work location. Then, they also observed negative coefficients on the predicted work location in the wage equation, providing strong support for the existence of wage gradients.

Darren Timothy (1994) estimated wage premia on each work location, along with information on individual worker characteristics, using the microdata from the 1990 Census for five large metropolitan areas. He observed that wages vary substantially across employment zones and this variation was significantly correlated with the average travel time of workers in each location.

He estimated the following semi-log wage equation by regression analysis using the Census data. The coefficient of each work place PUMA[7] (α) represents wage premia of each work place in the metropolitan area.

$$\ln(\text{Wage}) = \alpha X + \beta' Z$$

where X is a work zone specific dummy variable and Z is a vector of individual characteristics.

Then, using the same data, the mean commuting time of workers[8] in each workplace was calculated. Finally, a simple linear regression, where the independent variable is mean commuting time in each zone and the dependent variable is the wage equation coefficient for dummy of each zone, estimated correlation between wage differentials and commuting time in the metropolitan areas.

We duplicate his approach into the Los Angeles metropolitan area. Employing the individual data of the five counties from the 1990 Census and then from the 1980 Census, we estimate the wage equation for each of two occupation categories[9] separately.

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[7] Refer to p.8.

[8] Restricted to full time workers who worked for more than 48 weeks per a year and 35 hours per a week.

[9] The data was divided into two groups: high technical jobs and low technical jobs, based on types of occupation in the data. High technical jobs include managers, management related jobs, architects, engineers & scientists, social scientists, lawyers and artists. Low technical jobs include sales representatives, supervisors, secretaries & receptionists and clerical jobs.

3.4. Data

3.4.1. Census Micro Data

The Census Bureau provides this 5% sample of households, using data drawn from the 1990 and the 1980 Census of Population and Housing. The 5% Public Use Microdata Sample (PUMS) of the 1990 and 1980 Censuses was used for the estimation of the wage equation. This data provides information on both household and individual characteristics, including age, ethnicity, education, income, and employment.

We subtracted particular individual data from the sample, mainly based on PUMA and types of employment, in order to focus on office workers in the Los Angeles metropolitan area. The number of observations for high-technical (HT) jobs is 28,493 and the number for low-technical (LT) jobs is 23,549.

3.4.2. Public Use Microdata Area

Workplace locations in the metropolitan area are defined by using Public Use Microdata Areas (PUMAs), specified by each state with a minimum population of 100,000 using guidelines set by the Census Bureau. Residential PUMAs (RESPUMAs) are defined as subdivisions of place of work PUMAs (POWPUMAs)[10]. In this analysis, POWPUMAs are used for the subcenter boundaries.

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[10] For example, numbers of POWPUMAs and RESPUMAs of 1990 Census in the four counties in the Los Angeles metropolitan area are as follows.

	POWPUMAs	RESPUMAs
Orange County	7	7
Los Angeles County	15	58
Ventura County	1	5
Riverside County & San Bernardino County	5	15

Definitions of the PUMAs in the Los Angeles metropolitan area changed greatly between the 1990 Census and the 1980 Census. As shown in Table 3.1, in the 1990 Census, there were 28 POWPUMAs in the Los Angeles metropolitan area, whereas only 13 in the 1980 Census. In addition to the difference of the number of POWPUMAs, the area definitions in the two Censuses did not contain any compatibility with each other. Thus, a simple comparison between the data in 1990 and the data in 1980 is unfeasible.

Table 3.1a: 1990 Census PUMA Definition in the Los Angeles Metropolitan Area

Orange County	
4200	Santa Ana
4300	Laguna Beach
4400	Laguna Hills
4500	San Juan
4600	Fountain Valley
4700	Garden Grove
4800	Irvine
Los Angeles County	
5200	Burbank
5300	Glendale
5400	Monterey Park
5500	East LA
5600	Florence-Graham
5700	Lynwood
5800	El Monte
5900	Pomona
6000	Carson
6100	Inglewood
6200	Beverly Hills
6300	Pasadena
6400	San Gabriel Valley
6500	Los Angeles City
6600	Long Beach
Ventura County	
6700	Ventura Co.
Riverside County & San Bernardino County	
6800	Moreno Valley
6900	Riverside
7000	Rancho Cucamonga
7100	Ontario
7200	San Bernandino

Table 3.1b:1980 Census PUMA Definition in the Los Angeles metropolitan Area

Ventura County	
38	Oxnard City
39	Ventura Co.
Los Angeles County	
40	Los Angeles City
41	Long Beach City
42	Los Angeles Co.
Orange County	
43	Anaheim
44	Santa Ana
45	Garden Grove
46	Orange Co.
Riverside County & San Bernandino County	
47	San Bernandino City
48	San Bernandino Co.
49	Riverside City
50	Riverside Co.

3.5. Travel Time

In the 1990 Census, the average travel time for employees in each POWPUMA varies significantly from 21.6 minutes to 31.7 minutes across work zones, as shown in Table 3.2. Among PUMAs, Los Angeles City shows the longest travel time of 29.8 minutes, with an exception of 31.7 minutes in Pasadena. Also, the average travel time in Los Angeles County is the longest in the area, 28.3 minutes; this is significantly longer than any of the other four counties which shows the average travel time from 21.6 minutes to 24.1 minutes. This longer travel time in Los Angeles County suggests that it attracts workers from other counties to commute in, and consequently, the traffic congestion tends to be the highest in the metropolitan area.

In the 1980 Census, the average travel time varies between 16.4 minutes for Ventura County and 36.2 minutes for Riverside County. In Riverside County, however, only 27 observations for HT jobs and 22 for LT jobs were available; thus, the data in this PUMA is not quite sizable. Except Riverside County, Los Angeles City shows the longest average travel times (27.9 minutes) among subcenters. Correspondingly, Los Angeles County had the significantly longer average travel time relative to other counties. Therefore, both in the 1990 Census and the 1980 Census, it is proved that the larger center location maintained longer travel time, as a theory predicted.

Table 3.2: Tabulation of Travel Time in 1990 PUMA and 1980 PUMA

	1990 Census			1980 Census			%Chg
	POWPUMAs	T-Time	Ave_T	POWPUMAs	T-Time	Ave_T	
	Orange County						
1	4200 Santa Ana	26.8	24.1	44 Snta Ana	22.8	21.4	**12%**
	4300 Laguna Beach	22.9		46 Orange Co.	21.8		
	4500 San Juan	22.8		43 Anaheim	21.5		
	4600 Fountain Valley	22.6		45 Garden Grove	19.6		
	4400 Laguna Hills	23.1					
	4700 Garden Grove	23.8					
	4800 Irvine	26.5					
	Average	24.1			21.4		**12%**
	Los Angeles County						
2	5200 Burbank	27.2	28.3	42 Los Angeles Co.	24.9	24.9	**13%**
	5300 Glendale	26.6					
	5400 Monterey Park	27.7					
	5500 East LA	27.9					
	5600 Florence-Graham	29.4					
	5700 Lynwood	27.8					
	5800 El Monte	28.3					
	5900 Pomona	25.9					
	6000 Carson	28.3					
	6100 Inglewood	29.6					
	6200 Beverly Hills	31.7					
	6300 Pasadena	29.9					
	6400 San Gabriel Valley	27.0					
3	6500 Los Angles City	30.0	30.0	40 Los Angeles City	27.9	27.9	**8%**
4	6600 Long Beach	27.5	27.5	41 Long Beach City	23.7	23.7	**16%**
	Average	28.3			25.5		**11%**
	Ventura County						
5	6700 Ventura Co.	21.6	21.6	38 Oxnard City	17.1	16.78	**29%**
				39 Ventura Co.	16.4		
	Average	21.6			16.8		**29%**
	Riverside & San Bernardino Counties						
6	6800 Moreno Valley	23.1	23.1	50 Riverside Co.	36.2	36.2	**-36%**
7	6900 Riverside	22.2	22.2	49 Riverside City	17.0	17.0	**30%**
8	7000 Rancho Cucamonga	23.5	24.3	48 San Bernandino Co.	17.2	17.2	**41%**
	7100 Ontario	25.1					
9	7200 San Bernardino	22.2	22.2	47 San Bernandino City	18.1	18.1	**22%**
	Average	23.2		0.0	17.5		**33%**

As introduced above, area definitions of two Censuses are very different and incompatible with each other. However, in order to examine changes in travel time in the similar locations over 10 years, we consolidated two area definitions into 9 zones in Table 3.2. The center location, Los Angeles City, experienced the smallest increase in travel time (8%) in the area. Conversely, in the peripheral locations (Ventura County, and Riverside County/San Bernardino County) the average travel time increased approximately 30% over 10 years[11]. This longer travel times in these regions suggest that those subcenters expanded their border and experienced an increased influx of commuting traffic. Therefore, it is observed that the decentralization discussed in Chapter 2 has caused increased congestion at the points where this occurred.

3.6. Estimated Wage Equations

In Table 3.3 and 3.4, we present the coefficients of the wage equation estimated separately for HT workers and LT workers in the Los Angeles metropolitan area, using data from the 1990 Census and the 1980 Census. The equation consists of work zone specific variables (POWPUMAs) and individual characteristic variables. We will first discuss results from individual characteristics in each work location.

3.6.1. Individual Characteristics

In order to accurately estimate wage premia for each POWPUMA, the wage equation must control a range of individual characteristics in the wage gradient. Thus, we set up the following individual characteristic variables for the Z matrix of the wage

[11] The average travel time of Riverside & San Bernardino Counties in the 1980 Census does not include Riverside County (50), since this data is not sizable.

equation. We estimated these parameters separately for HT workers and LT workers, using the 1980 Census data and the 1980 Census data. Estimated coefficients are shown in Table 3.3 and 3.4.

Individual Characteristic Variables

1) Age (entered as a quartic function: age, age^2, age^3, age^4)
2) Education (dummy variables for the highest degree obtained)
3) Race (dummy variables for Black, Asian and Hispanic)
4) Gender dummy
5) Marital status (dummy variables for married man and woman separately)
6) Veteran status dummy (only for 1990)
7) English ability (dummy variables for four different levels)
8) Disability (dummies for 3 types of disability in 1990 and 2 types in 1980)
9) Industry (dummies for 4 classes)
    1 Manufacturing
    2 Finance, Insurance, and Real Estate (default)
    3 Business & Repair Services
    4 Professional & Related Services
10) Occupation (dummies for 11 classes)
    1 Managers (default for high technical jobs)
    2 Management Related
    3 Architects
    4 Engineers & Scientists
    5 Social Scientist
    6 Lawyers
    7 Artists
    8 Sales Representatives (default for low technical jobs)
    9 Supervisors
    10 Secretaries & Receptionists
    11 Clerical

As a result of estimate using the 1980 Census data, we found that the parameters for individual characteristics are not significantly different from those in the 1990 Census (see Table 3.4). One particular point we could mention between the two data is that the highest growth of wage premia among all industries was in the finance, insurance and real estate (FIRE) sector; this is reflecting the structural changes of the industries toward financial businesses in the area. Additionally, the following points can be noted from this table with respect to the 1990 Census data:

- The age variables have positive effects on both occupational classes, but about 50% more on LT jobs.
- The education variables suggest that higher education guarantees a higher wage for HT jobs, but not always for LT jobs. Routinely, however, highly educated people work in highly technical fields.
- Being female has a negative impact on wage. The effect is greater for married female, married men have about 40% higher wage premia than married women for both occupational classes.
- Among minorities, Hispanics have the highest wage premia; they are followed by Asians and Blacks.
- As expected, higher English skills guarantee higher wages for both occupations.
- The manufacturing industry pays the highest salary for both HT and LT workers among industry groups.
- In the HT occupational class, only engineers/scientists and lawyers have higher wage premia than managers. On the other hand, in the LT class, sales representatives receive the highest salary.

3.6.2. Wage Premia

1) 1990 Census

The wage premia for each POWPUMA is shown in Table 3.3; the coefficients of PUMA zones represent the percentage difference in wages between Los Angeles City and the other POWPUMA. Wages in Los Angeles City are higher by 24.7% for HT jobs and by 22.5% for LT jobs than wages in San Bernardino, where the smallest wage premia was observed in the metropolitan area. On the other hand, Burbank and Beverly Hills show slightly higher wage premia for HT jobs (3.0% and 5.7% respectively) but all other zones have wage premia significantly smaller than that in Los Angeles City, particularly at the urban fringe.

Among five counties, Los Angeles County shows the highest Average wage premia in the metropolitan area (-6.5%) for both HT jobs and LT jobs. Whereas Ventura County, and Riverside/San Bernardino Counties shows significantly smaller average premia for both job classes: -11.8% for HT jobs and -16.6% for LT jobs in Ventura County, and -17.3% and -18.3% respectively in the Riverside County/San Bernardino County. On the other hand, Orange County shows insignificantly smaller average wage premia, -10.0% and -8.8% respectively.

These findings demonstrates a significant wage variation in the Los Angeles metropolitan area. In addition, the extreme edge of the metropolitan area shows the highest deviation in its wage premia. Finally, the average wage premia of each county indicates that the peripherally located counties have smaller wage premia. Thus, an incentive exists for the cost sensitive firms to locate farther from the center in order to minimize their wage expenses.

In the previous section, the decentralization of work locations was already observed through the travel time analysis as a long term trend in the Los Angeles metropolitan area. This trend will continue in the future, as far as differences in wage premia exist among work locations.

Table 3.3a: Wage Equation Coefficients of High-Tech Workers by 1990 Census

Variables	Coefficients	t-Statistics	Variables	Coefficients	t-Statistics
age	0.1934024	7.288	puma1 (4200)	-0.0696699	-3.361
age^2	-0.0046482	-5.077	puma2 (4300)	-0.2076220	-3.996
age^3	0.0000521	3.863	puma3 (4400)	-0.0131219	-0.316
age^4	-0.0000002	-3.286	puma4 (4500)	-0.1038770	-2.552
highschool	0.0964762	5.053	puma5 (4600)	-0.0857424	-2.012
postsecondary	0.1827872	10.191	puma6 (4700)	-0.1670777	-4.528
associate	0.2054675	10.489	puma7 (4800)	-0.0501145	-5.442
bachelor	0.3735745	20.978	puma8 (5200)	0.0302864	1.520
master	0.4660672	24.380	puma9 (5300)	-0.0312168	-1.123
professional	0.5224096	18.640	puma10 (5400)	-0.1409714	-3.381
doctor	0.5485403	19.857	puma11 (5500)	-0.1333634	-1.690
female	-0.1249625	-12.299	puma12 (5600)	-0.1225358	-1.831
married	0.1887320	21.999	puma13 (5700)	-0.1040841	-1.770
marriedfem	-0.1960699	-15.246	puma14 (5800)	-0.1627680	-3.542
black	-0.1242661	-7.983	puma15 (5900)	-0.1132845	-3.269
asian	-0.0673671	-6.768	puma16 (6000)	-0.0266845	-0.798
hispanic	-0.0534590	-4.798	puma17 (6100)	-0.0332926	-0.592
military	-0.0110773	-2.341	puma18 (6200)	0.0566394	2.714
english1	0.2593139	3.508	puma19 (6300)	-0.0623311	-2.615
english2	0.3735202	5.254	puma20 (6400)	-0.0508395	-5.932
english3	0.4925326	7.011	puma22 (6600)	-0.0741492	-4.459
english4	0.5934518	8.434	puma23 (6700)	-0.1177117	-6.815
disability1	-0.1588486	-7.853	puma24 (6800)	-0.0484029	-0.526
disability2	0.0394908	0.585	puma25 (6900)	-0.2292118	-11.756
disability3	-0.0801155	-3.381	puma26 (7000)	-0.1717490	-4.013
industry2	0.0247671	2.794	puma27 (7100)	-0.1706232	-4.418
industry9	-0.0261626	-2.023	puma28 (7200)	-0.2472671	-12.667
industry8	-0.0603015	-6.163	constant	-0.8342679	-2.932
occupation2	-0.1102548	-13.110			
occupation3	-0.0822527	-2.381			
occupation4	0.0021001	0.242			
occupation5	-0.5326338	-36.821			
occupation6	0.1795496	6.986	Adj-R2	0.3632	
occupation7	0	-11.588	Observation	28493	

Table 3.3b: Wage Equation Coefficients of Low-Tech Workers by 1990 Census

Variables	Coefficients	t-Statistics	Variables	Coefficients	t-Statistics
age	0.2558369	12.712	puma1 (4200)	-0.0362948	-1.839
age^2	-0.0069997	-9.761	puma2 (4300)	-0.1286011	-2.808
age^3	0.0000848	7.852	puma3 (4400)	-0.1061559	-2.777
age^4	-0.0000004	-6.671	puma4 (4500)	-0.0714696	-1.595
highschool	0.0916400	7.163	puma5 (4600)	-0.0678359	-1.655
postsecondary	0.1341245	10.680	puma6 (4700)	-0.1549459	-4.070
associate	0.1338179	8.880	puma7 (4800)	-0.0517974	-5.417
bachelor	0.2644005	18.752	puma8 (5200)	-0.0057320	-0.253
master	0.4198185	19.410	puma9 (5300)	-0.0365894	-1.468
professional	0.2965344	7.028	puma10 (5400)	-0.0536805	-1.559
doctor	0.4132273	4.762	puma11 (5500)	-0.1732622	-2.814
female	-0.0389391	-3.675	puma12 (5600)	-0.0746935	-1.152
married	0.2240711	19.731	puma13 (5700)	-0.0597656	-1.083
marriedfem	-0.2192599	-16.199	puma14 (5800)	-0.0890734	-1.997
black	-0.1010679	-7.880	puma15 (5900)	-0.1230630	-3.082
asian	-0.0576700	-5.953	puma16 (6000)	-0.0750042	-2.121
hispanic	-0.0236769	-2.432	puma17 (6100)	-0.1188689	-2.181
military	-0.0306911	-4.835	puma18 (6200)	-0.0087506	-0.406
english1	0.1736388	3.268	puma19 (6300)	-0.0798615	-3.268
english2	0.3371214	6.655	puma20 (6400)	-0.0718497	-7.917
english3	0.4795554	9.618	puma22 (6600)	-0.0060506	-0.310
english4	0.5534406	11.047	puma23 (6700)	-0.1655221	-9.138
disability1	-0.1063910	-4.985	puma24 (6800)	-0.1481913	-1.804
disability2	-0.0410391	-0.716	puma25 (6900)	-0.2169435	-12.354
disability3	-0.0529494	-2.578	puma26 (7000)	-0.1881014	-3.922
industry2	0.0050938	0.667	puma27 (7100)	-0.1383840	-3.227
industry9	-0.0879376	-7.531	puma28 (7200)	-0.2246382	-12.313
industry8	0.0013354	0.133	constant	-1.2044950	-5.798
occupation9	-0.1120105	-6.835			
occupation10	-0.2413133	-23.622	Adj-R2	0.3382000	
occupation11	0	-34.186	Observation	23549	

2) 1980 Census

Wage equation coefficients of the 1980 Census are reported in Table 3.4. In this table, among Los Angeles City and the outlying work zones, the largest wage differentials are observed in San Bernandino County (15.5% for HT jobs and 19.2% for LT jobs). (Differentials are 8.9% and 14.3% in Ventura County, and 5.4% and 13.7% respectively in Riverside County). On the other hand, work locations in Orange County have higher wage premia than those counties at the urban fringe. In particular, for HT jobs, Orange County

Table 3.4a: Wage Equation Coefficients of High-Tech Workers by 1980 Census

Variables	Coefficients	t-Statistics	Variables	Coefficients	t-Statistics
age	0.1055947	2.736	occupation2	-0.0293664	-1.692
age^2	-0.0013474	-1.015	occupation3	-0.0452843	-0.567
age^3	0.0000029	0.148	occupation4	0.0219512	1.290
age^4	0.0000000	0.093	occupation5	-0.3544604	-12.444
highschool	-0.4873824	-5.351	occupation6	0.1106146	2.744
postsecondary	-0.5077847	-6.026	occupation7	-0.0018221	-0.079
associate	-0.3421963	-8.509	puma1 (38)	-0.1275387	-1.431
bachelor	-0.2570408	-14.168	puma2 (39)	-0.0892535	-1.784
master	-0.1516643	-6.161	puma4 (40)	-0.0445726	-1.166
professional	-0.1702952	-9.206	puma5 (41)	-0.0134042	-0.910
doctor	-0.0835960	-3.445	puma6 (43)	-0.0128348	-0.354
female	-0.2160999	-10.200	puma7 (44)	-0.0347661	-0.882
married	0.1681163	9.908	puma8 (45)	-0.0723621	-0.868
marriedfem	-0.2297686	-8.376	puma9 (46)	-0.0012099	-0.061
black	-0.0806190	-2.554	puma10 (47)	-0.1180124	-1.680
asian	-0.0457352	-1.810	puma11 (48)	-0.1554719	-3.729
hispanic	-0.0625967	-2.399	puma12 (49)	-0.1369775	-2.063
english1	0.2374651	1.229	puma13 (50)	-0.0540988	-0.461
english2	0.4439934	2.369	constant	-0.5170069	-1.179
english3	0.5466201	2.952			
english4	0.6483877	3.496			
disability1	-0.1878258	-5.593			
disability2	-0.0820919	-0.858			
industry2	0.1212454	6.792			
industry9	0.1008106	3.711	Adj-R2	0.190	
industry8	0.0411968	1.948	Observation	11425	

Table 3.4b: Wage Equation Coefficients of Low-Tech Workers by 1980 Census

Variables	Coefficients	t-Statistics	Variables	Coefficients	t-Statistics
age	0.1808454	6.256	industry2	0.0529862	4.036
age^2	-0.0047660	-4.551	industry9	-0.0298674	-1.210
age^3	0.0000551	3.474	industry8	0.0115463	0.619
age^4	-0.0000002	-2.785	occupation9	-0.0917306	-3.349
highschool	-0.1913582	-2.544	occupation10	-0.2130899	-10.825
postsecondary	-0.1007256	-1.365	occupation11	-0.2576857	-15.161
associate	-0.1277043	-4.260	puma1 (38)	-0.0910243	-1.020
bachelor	-0.1006042	-5.898	puma2 (39)	-0.1427846	-3.011
master	-0.0809214	-3.937	puma4 (40)	-0.0673415	-1.943
professional	-0.0609189	-3.250	puma5 (41)	-0.0634405	-4.713
doctor	-0.0281033	-1.051	puma6 (43)	-0.0528371	-1.444
female	-0.0871303	-4.519	puma7 (44)	-0.0353477	-1.092
married	0.2168567	10.061	puma8 (45)	-0.1454691	-2.163
marriedfem	-0.2586946	-10.391	puma9 (46)	-0.0804695	-4.330
black	-0.0700087	-3.125	puma10 (47)	-0.1920135	-3.241
asian	-0.0184961	-0.877	puma11 (48)	-0.1862285	-5.058
hispanic	-0.0238264	-1.198	puma12 (49)	-0.0753037	-1.335
english1	0.2829579	2.019	puma13 (50)	0.1065740	0.837
english2	0.4462781	3.353	constant	-0.8992536	-2.892
english3	0.5344388	4.065			
english4	0.5892680	4.467			
disability1	-0.0206534	-0.609	Adj-R2	0.190	
disability2	-0.1820125	-1.782	Observation	11425	

shows the average wage premia to be only 3% less than the premia in Los Angeles City. Thus, wage premia were smaller in the subcenters of those counties located at the fringe of the metropolitan area. In the metropolitan area, Los Angeles City had the highest wage premia, although the subcenter, Orange County, showed almost same premia (-0.1%) for HT jobs.

The preceding analysis finds concrete wage variations in the metropolitan area. Accordingly, results show that smaller wage premia existed at locations farther from the center, as we estimated using data from the 1990 Census. Compared to the 1990 Census, however, wages are found to vary smaller.

3.7. Travel Time and Wage Differentials

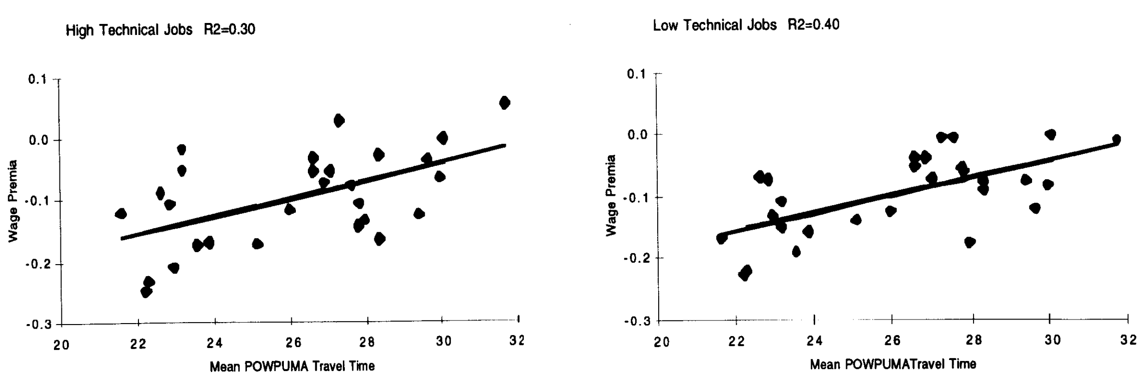
1) 1990 Census

We next estimated the following wage equations using average travel time and wage premia in each POWPUMA, both of which were estimated previously. The results of our estimates are shown in Table 3.5. The coefficients on travel time are significant and positive, as predicted by theory, with R^2 of 0.3 for HT jobs and 0.4 for LT jobs. Figure 3.3 shows the distribution of wage premia for each POWPUMA against average POWPUMA travel time; the lines represent the fitted value of a simple linear regression of travel time on wage premia. These figures show significant and positive correlation between the wage premia and average travel time.

Table 3.5: Results of Regression by the 1990 Census

	High-Tech Workers	Low-Tech Workers
Coefficients	0.014454	0.013997
t-Statistics	3.339	4.179
R Square	0.300144	0.401724
Adj-R Square	0.273227	0.378714
Observation	28	28

Figure 3.3: Wage Premia and Travel Time (1990 Census)



The coefficients on the POWPUMA average travel time variable are 0.014454 for HT workers and 0.013997 for LT workers. These coefficients represent the semi-elasticity of the hourly wage with respect to two additional minutes of commuting time, since workers have to travel to and from work each day. Thus, workers place a value of 30 times of the estimated coefficients. In the Los Angeles metropolitan area, therefore, HT workers value their commuting time at 43% of their wage, whereas LT workers value theirs at 42%.

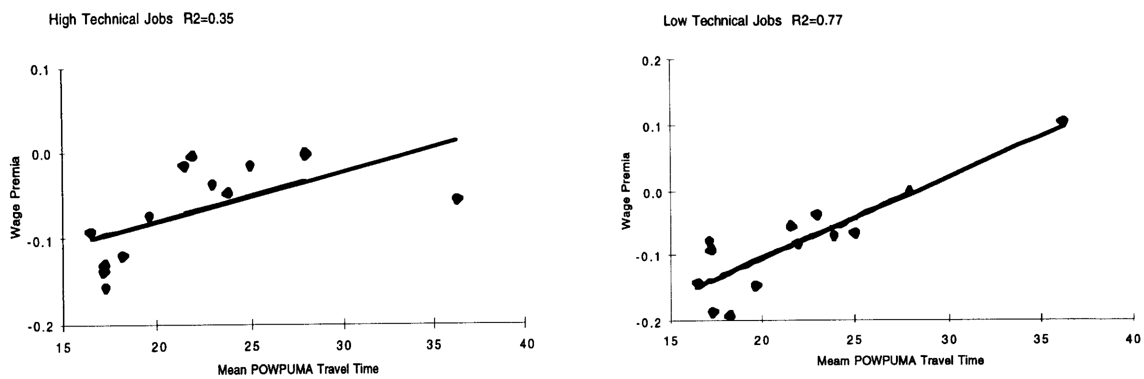
2) 1980 Census

The estimated wage equation of the 1980 is shown in Table 3.6. Also, in Figure 3.4 , the wage premia for each POWPUMA is plotted against average travel time. The wage premia is significantly and positively correlated with average POWPUMA travel time for LT jobs, with R^2 of 0.77. For HT workers, however, the equation is less significant with a smaller value of R^2, 0.35. This low correlation is mainly due to the extremely high travel time in Riverside County caused by small number of observations from the PUMA zone in the data set. This defect in the data also affected travel time valuation; HT workers value their commuting time only 17% of their wage, whereas LT workers 36%.

Table 3.6: Results of Regression by the 1980 Census

	High-Tech	Low-Tech
Coefficients	0.005813	0.012646
t-Statistics	6.151	2.432
R Square	0.349739	0.774776
Adj-R Square	0.290624	0.754301
Observation	13	13

Figure 3.4: Wage Premia and Travel Time (1980 Census)



3.8. Conclusion

Travel time and wages are found to vary significantly within the Los Angeles metropolitan area. Particularly in subcenters at the peripheral locations, wage premia tended to be the smallest, and shorter travel time was observed. On the other hand, we noticed high wage premia and longer travel time in downtown locations. The average travel time in each work location was positively and significantly correlated with wage premia in most locations, as theory predicted. Therefore, an equilibrium condition exists between subcenters and between subcenters and downtown work locations.

It is also observed by comparing the results using the 1990 Census to those using the 1980 Census, that travel time increased more in peripheral work locations with lower wages. This extending travel time in these regions suggests that those subcenters expanded their border and increased the population commuting in those subcenters. Employment decentralization, therefore, continues under the equilibrium condition.

4. Office Decentralization, Wages and Travel Time

4.1. Introduction

In the previous two chapters, we looked at the facts and causes of decentralization. In Chapter 2, we analyzed the history of the 43 office markets in the Los Angeles metropolitan area based on the data from a commercial brokerage firm. Through this analysis, we observed rapid growth of suburban subcenters, in particular peripheral locations. At the same time, urban centers in Los Angeles lost their share of the metropolitan market. Thus, we concluded that decentralization is a long term trend of the area.

In Chapter 3, we focused on the causes of decentralization, in particular commuting congestion and wages. Using the data from the 1990 Census and the 1980 Census, the average travel time and wage premia were estimated for each place of work PUMA. Significant positive correlation was found between travel time and wages in each POWPUMA. In addition, wage premia tended to be smaller in the fringe locations. Therefore, there is an incentive for firms to decentralize in order to decrease their wage payments. Actually, faster growing travel time in the peripheral locations suggested that those locations grew more rapidly than the urban centers.

In this chapter, we will estimate relationships between these facts and causes of decentralization in the metro area. Finally, we derive an answer to one of our questions in this thesis: "Is growth of subcenters related to their travel time and wages?" In order to compare real estate data directly to travel time and estimated wage premia, we first merge and tabulate real estate data of 43 submarkets into 28 place-to-work PUMA zones[12] that were defined in the 1990 Census. Thereafter, two equations are estimated in terms of scale and growth of POWPUMAs, using average travel time and estimated wage premia as variables as well as real estate data. By estimating these equations we will find not only an answer to our question, but we will also be able to predict growth of subcenters. In the next chapter, we will forecast future growth of subcenters using these equations.

4.2. Scale of Subcenters, and Travel Time and Wage Premia

First, We compute two relationships: one, between scale of subcenters and travel time, and two, between scale of subcenters and wage premia. Urban economic theory predicts that larger centers should have longer travel time and bigger wage premia. We will statistically test this theory in this section, using the tabulated real estate data, the average travel time, and estimated wage premia of each POWPUMA of the 1990 Census.

4.2.1. Equations

In the monocentric city model, the city border must be decided by the scale of the work center. As the scale of subcenters increases, more workers commute from residential locations, and the subcenter border moves out further from the center. Longer travel time should be capitalized in wages. The following simple linear equations explain these relationships. The equations are tested in terms of average travel time and wage premia separately; additionally we have separate two wage premia: one for HT workers and the other for LT workers.

[12] We tabulated all properties tracked by CB Commercial into POWPUMA zones, based on their addresses and zip codes. As a result, we found no properties located in the three POWPUMA zones: 5600-5800, Thus, the number of work locations used in this chapter is 25.

$$T_i = \alpha + \beta OC_{i90} \quad \text{and} \quad W_i = \alpha + \beta OC_{i90}$$

where T_i is the average travel time of each subcenter, W_i is the wage premia of each subcenter, and OC_{i90} is the total occupied office stock of each subcenter in 1990. The occupied stock variable is used as a parameter for scale of subcenters.

4.2.2. Results of Estimates

1) Travel Time

Table 4.1a shows the results of estimation of the scale equation in terms of the average travel time. The results suggest that scale of subcenters is significantly and positively correlated with average travel time, with R^2 of 0.12. This lower R^2 means that each subcenter has a different transportation system, therefore, an accessibility varies over subcenters.

Table 4.1a: Results of Estimation: $T_i = \alpha + \beta OC_{i90}$

Regression Statistics			
Multiple R	0.3487867		
R Square	0.1216522		
Adjusted R Square	0.0834631		
Standard Error	2.8013320		
Observations	25		
Parameter Estimates			
Term	**Coefficients**	**Std Error**	**t Stat**
Intercept (α)	25.3984339	0.6126051	41.4597186
OC_i90	0.0000604	0.0000338	1.7848042

2) Wage Premia

The scale equation was estimated in terms of wage premia for HT workers (WHT_i) and wage premia for LT workers (WLT_i) separately. We report the results for HT workers on Table 4.1b and the results for LT workers on Table 4.1c. Scale of subcenters is

Table 4.1b: Results of Estimation: $WHT_i = \alpha + \beta OC_{i90}$

Regression Statistics			
Multiple R	0.3050196		
R Square	0.0930370		
Adjusted R Square	0.0536038		
Standard Error	0.0777671		
Observations	25		
Parameter Estimates			
Term	**Coefficients**	**Std Error**	**t Stat**
Intercept (α)	-0.1021970	0.0170064	-6.0093331
OC_i90	0.0000014	0.0000009	1.5360200

correlated with wage premia of both occupation classes, but less significantly with HT workers than with LT workers. As was in the case of estimation by travel time, we observed low R^2 values: 0.09 for HT workers and 0.14 for LT workers. These low R^2s are again explained by the different accessibility to each subcenter. The higher R^2 for HT workers implies that the work force of HT workers is less elastic for employers, since they have rather unsubstitutable skills.

Table 4.1c: Results of Estimation: $WLT_i = \alpha + \beta OC_{i90}$

Regression Statistics			
Multiple R	0.3773083		
R Square	0.1423616		
Adjusted R Square	0.1050729		
Standard Error	0.0615204		
Observations	25.0000000		
Parameter Estimates			
Term	**Coefficients**	**Std Error**	**t Stat**
Intercept (α)	-0.1053278	0.0134535	-7.8290239
OC_i90	0.0000015	0.0000007	1.9539262

4.2.3. Comparison: Actual and Predicted

Table 4.2 shows actual and predicted value of average travel time and wage premia. Average differences between the actual figures and the predicted figures for each county are also mentioned. Among four regions, Los Angeles County has the largest difference for all three dependent variables; the actual figures are substantially bigger than the predicted values. These large positive differences clearly suggest that congestion externalities in the region create additional costs to the office firms located there. In contrast, the counties at the urban fringe: Ventura County, Riverside County and San Bernardino County, maintain considerably large negative differences that imply more efficient transportation systems available. Therefore, an incentive still exists for decentralization, particularly into those three counties, although rapid growth of office markets and travel time was already recognized in the previous chapters.

The worst location in terms of congestion is Beverly Hills. Longer travel time causes higher wage premia, in particular for HT workers. Burbank also shows considerably higher actual wage premia than predicted, but with modest longer travel time. On the other hand, Riverside and San Bernardino are the two best locations for firms to locate in terms of both travel time and wages. These two locations were also noticed in Chapter 3, as the two subcenters with the fastest growth of travel time over 10 years from 1980. There exists one subcenter worth mentioning here, that is Los Angeles City. This location contains the downtown office market which shares over 20% of total existing office stock in Los Angeles County. It was previously observed to have the longest travel time and the highest wage premia for both the 1980 and 1980 Censuses, with a very few exceptions. However, only Los Angeles City shows smaller actual travel time in Los Angeles County, and it also shows smaller actual wage premia for both HT and LT jobs. This is due to the area's highway system; Los Angeles City is located at the center of the highway system. Therefore, downtown still maintains an incentive for firms to locate here.

Table 4.2: Travel Time & Wage Premia: Actual and Predicted

POWPUMA	T_i			WHT_i			WLT_i		
	Actual	Predict	Diff	Actual	Predict	Diff	Actual	Predict	Diff
Orange Co									
42 Santa Ana	26.81	25.70	1.11	-0.070	-0.095	0.025	-0.036	-0.098	0.062
43 Laguna Beach	22.89	25.41	-2.53	-0.208	-0.102	-0.106	-0.129	-0.105	-0.024
44 Laguna Hills	23.12	25.45	-2.34	-0.013	-0.101	0.088	-0.106	-0.104	-0.002
45 San Juan	22.78	25.42	-2.64	-0.104	-0.102	-0.002	-0.071	-0.105	0.033
46 Fountain Valley	22.57	25.44	-2.87	-0.086	-0.101	0.016	-0.068	-0.104	0.037
47 Garden Grove	23.82	25.42	-1.61	-0.167	-0.102	-0.066	-0.155	-0.105	-0.050
48 Irvine	26.54	27.23	-0.69	-0.050	-0.058	0.008	-0.052	-0.061	0.009
Ave. Difference			**-1.65**			**-0.005**			**0.009**
LA Co									
52 Burbank	27.23	25.58	1.66	0.030	-0.098	0.128	-0.006	-0.101	0.095
53 Glendale	26.55	25.63	0.93	-0.031	-0.097	0.066	-0.037	-0.100	0.063
54 Monterey Park	27.74	25.50	2.23	-0.141	-0.100	-0.041	-0.054	-0.103	0.049
58 El Monte	28.31	25.48	2.83	-0.163	-0.100	-0.063	-0.089	-0.103	0.014
59 Pomona	25.91	25.43	0.48	-0.113	-0.101	-0.012	-0.123	-0.105	-0.019
60 Carson	28.32	25.41	2.91	-0.027	-0.102	0.075	-0.075	-0.105	0.030
61 Inglewood	29.60	25.44	4.16	-0.033	-0.101	0.068	-0.119	-0.104	-0.014
62 Beverly Hills	31.72	25.71	6.00	0.057	-0.095	0.151	-0.009	-0.098	0.089
63 Pasadena	29.93	25.71	4.23	-0.062	-0.095	0.033	-0.080	-0.098	0.018
64 San Gabriel Valley	26.98	26.86	0.12	-0.051	-0.067	0.016	-0.072	-0.070	-0.002
65 Los Angeles City	30.03	30.27	-0.24	0.000	0.014	-0.014	0.000	0.012	-0.012
66 Long Beach	27.54	25.73	1.81	-0.074	-0.094	0.020	-0.006	-0.097	0.091
Ave. Difference			**2.26**			**0.036**			**0.034**
Ventura Co									
67 Ventura	21.57	25.63	-4.06	-0.118	-0.097	-0.021	-0.166	-0.100	-0.066
Ave. Difference			**-4.06**			**-0.021**			**-0.066**
Riverside/San Bernardino Co									
68 Moreno Valley	23.12	25.41	-2.30	-0.048	-0.102	0.053	-0.148	-0.105	-0.043
69 Riverside	22.24	25.65	-3.41	-0.229	-0.096	-0.133	-0.217	-0.099	-0.118
70 R. Cucamonga	23.49	25.45	-1.96	-0.172	-0.101	-0.071	-0.188	-0.104	-0.084
71 Ontario	25.05	25.44	-0.39	-0.171	-0.101	-0.069	-0.138	-0.104	-0.034
72 San Bernandino	22.16	25.61	-3.45	-0.247	-0.097	-0.150	-0.225	-0.100	-0.124
Ave. Difference			**-2.30**			**-0.074**			**-0.081**

4.2.4. Findings

In theory, larger subcenters must have longer travel time and longer traveling commuters should be compensated by higher wages. This theory was verified in the Los Angeles metropolitan area through the estimation of our scale equation; positive correlation with occupied stock was found in terms of average travel time and wage premia. At the same time, however, the lower fit of the equation implies that travel time of subcenters is influenced not only by their size, but also by their transportation system. In addition, size of office stock represents only one sector of economy; wages of each subcenter are more affected by its total employment.

Furthermore, incentives of future decentralization for firms were observed by comparing actual travel time and wage premia to predicted figures. According to this comparison, the winners may be Riverside and San Bernardino, and the losers would be Beverly Hills and Burbank. Not surprisingly, Los Angeles City is still an attractive location for firms. This finding is actually consistent with real estate data in Chapter 2, that disclosed the downtown market maintained a stable share of net absorption in the area, although the figure for Los Angels County declined as a whole.

4.3. Growth of Subcenters, and Travel Time and Wage Premia

In the previous section, we observed the existence of intraurban wage gradients in the Los Angeles metropolitan area: the bigger a subcenter is, the longer travel time it has; the longer workers commute, the higher their wages are. Then, how is the growth of subcenters related to travel time and wages? Theory says that growing subcenters must have a shorter travel time and smaller wages. As already we disclosed in Chapter 3, the subcenters with shorter travel time had greatly increased their travel time between 1980 and 1990. These subcenters tended to have growing office submarkets, as we observed in Chapter 2. In this section, we try to find empirical relationships between the growth of subcenters, and travel time and wages.

4.3.1. Equations

Using the same data as we used for the scale equation, the following growth equations are estimated statistically. We define total net office absorption of a subcenter between 1988 and 1994 divided by total stock of the same zone as a parameter of measuring growth of a zone:

$$AB_i88\text{-}94 \,/\, OC_i90 = \alpha + \beta T_i + \tau R_i90 \quad , \text{ and,}$$

$$AB_i88\text{-}94 \,/\, OC_i90 = \alpha + \beta W_i + \tau R_i90$$

where ABi88-94 is the total net absorption of each subcenter between 1988 and 1990, OCi90 is the total occupied office stock of each subcenter in 1990 and Ri90 is the asking rent of each subcenter in 1990.

4.3.2. Results of Estimates

1) Travel Time

The results of estimate of growth equation in terms of travel time are presented on Table 4.3a. As theory predicted, a negative and highly significant correlation with R^2 of 0.3 was observed between travel time and growth of subcenters. A much higher R^2 than that for the scale equation implies that travel time is more strongly related to the growth of subcenters than to scale. This is due to the fact that absorption measures marginal influence as opposed to scale which is product of history.

Table 4.3a: Results of Estimation:
$AB_i88\text{-}94 \,/\, OC_i90 = \alpha + \beta T_i + \tau R_i 90$

Regression Statistics			
Multiple R	0.5457645		
R Square	0.2978589		
Adjusted R Square	0.2340279		
Standard Error	0.2579233		
Observations	25		
Parameter Estimates			
Term	**Coefficients**	**Std Error**	**t Stat**
Intercept (α)	1.3652246	0.4678095	2.9183343
T_i	-0.0661999	0.0216816	-3.0532764
R_i	0.0288000	0.0161109	1.7876122

2) Wage Premia

As was the case for the scale equation, the growth equation was estimated for HT workers and LT workers separately. Table 4.3a and Table 4.3b show the results of estimates. Wage premia for both occupations was correlated with growth of subcenters positively and significantly above the 99% level for HT workers and the 95% level for the LT workers, with R^2 of 0.24 and 0.18 accordingly. Those results are exactly the opposite of the results for the scale equation.

Table 4.3b: Results of Estimation:
$AB_i88\text{-}94 \,/\, OC_i90 = \alpha + \beta WHT_i + \tau R_i 90$

Regression Statistics			
Multiple R	0.4918649		
R Square	0.2419310		
Adjusted R Square	0.1730157		
Standard Error	0.2679988		
Observations	25		
Parameter Estimates			
Term	**Coefficients**	**Std Error**	**t Stat**
Intercept (α)	-0.5241192	0.3882201	-1.3500569
WHT_i	-2.2238570	0.8398418	-2.6479474
R_i	0.0275225	0.0170488	1.6143352

Table 4.3c: Results of Estimation:
$$AB_i88\text{-}94 \;/\; OC_i90 = \alpha + \beta WLT_i + \tau R_i 90$$

Regression Statistics			
Multiple R	0.4256772		
R Square	0.1812011		
Adjusted R Square	0.1067648		
Standard Error	0.2785269		
Observations	25		
Parameter Estimates			
Term	**Coefficients**	**Std Error**	**t Stat**
Intercept (α)	-0.8072633	0.5380875	-1.5002455
WLT_i	-2.9446792	1.3357548	-2.2045059
R_i	0.0381198	0.0220592	1.7280666

3) Rents

In all three equations, the coefficients of the rent variable are positive; this positive sign implies that higher rents contribute to the growth of subcenters. At a glance, these results seem to be inconsistent with the real world where people are concerned with costs. However, office space is seldom rented only by price, quality and location are often more important measures for tenants. Therefore, the positive sign on the coefficients is quite reasonable if rent is a proxy for all office quality measures. However, rents are less significantly correlated with growth of subcenters than travel time and wage premia.

4.3.3. Analysis of the Past Growth: Actual and Predicted

In Table 4.4, we report the predicted growth figures between 1988 and 1994 for 25 POWPUMA zones, together with actual growth experienced during these years. We calculated these figures using three previously generated equations. The most noticeable trend on this table is that the actual growth in Riverside County/San Bernardino County is much faster than predicted. Large positive average differences in Riverside County/San Bernardino County suggest that, in the six years between 1988 and 1994, subcenters in this region grew so fast that travel time and wage premia will increase further in the future. Among these subcenters, however, only San Bernardino shows negative figures; this submarket which ranked as one of the best subcenters to locate in has not grown enough in the this time period.

We can categorize the subcenters which demonstrate negative differences into two

Table 4.4: Actual and Predicted Growth

POWPUMA		T_i			WHT_i			WLT_i		
	Act.G	Ti	Pre.G	Diff	WHTi	Pre.G	Diff	WLTi	Pre.G	Diff
Orange Co										
42 Santa Ana	14%	26.8	11%	3%	-0.07	13%	1%	-0.04	-1%	15%
43 Laguna Beach	92%	22.9	41%	50%	-0.21	48%	44%	-0.13	32%	60%
44 Laguna Hills	23%	23.1	41%	-18%	-0.01	5%	17%	-0.11	26%	-4%
45 San Juan	34%	22.8	48%	-14%	-0.10	30%	4%	-0.07	23%	11%
46 Fountain Valley	-8%	22.6	38%	-45%	-0.09	15%	-23%	-0.07	6%	-14%
47 Garden Grove	-15%	23.8	28%	-43%	-0.17	32%	-47%	-0.15	30%	-45%
48 Irvine	26%	26.5	20%	7%	-0.05	15%	12%	-0.05	12%	14%
Ave. Difference				**-9%**			**1%**			**5%**
LA Co										
52 Burbank	26%	27.2	24%	2%	0.03	6%	21%	-0.01	11%	15%
53 Glendale	41%	26.6	36%	5%	-0.03	26%	14%	-0.04	29%	11%
54 Monterey Park	38%	27.7	11%	28%	-0.14	34%	4%	-0.05	11%	27%
58 El Monte	-1%	28.3	-1%	1%	-0.16	31%	-32%	-0.09	11%	-11%
59 Pomona	1%	25.9	14%	-13%	-0.11	20%	-19%	-0.12	20%	-19%
60 Carson	-26%	28.3	-2%	-24%	-0.03	1%	-27%	-0.08	7%	-33%
61 Inglewood	-28%	29.6	-15%	-13%	-0.03	-2%	-26%	-0.12	14%	-42%
62 Beverly Hills	5%	31.7	14%	-9%	0.06	18%	-14%	-0.01	37%	-33%
63 Pasadena	9%	29.9	3%	6%	-0.06	23%	-14%	-0.08	28%	-19%
64 San Gabriel Valley	23%	27.0	16%	7%	-0.05	15%	8%	-0.07	18%	5%
65 Los Angeles City	7%	30.0	9%	-1%	0.00	15%	-8%	0.00	13%	-6%
66 Long Beach	11%	27.5	24%	-13%	-0.07	31%	-20%	-0.01	13%	-3%
Ave. Difference				**-2%**			**-9%**			**-9%**
Ventura Co										
67 Ventura	18%	21.6	45%	-27%	-0.12	23%	-5%	-0.17	37%	-18%
Ave. Difference				**-27%**			**-5%**			**-18%**
Riverside/San Bernardino Co										
68 Moreno Valley	60%	23.1	23%	37%	-0.05	-4%	64%	-0.15	15%	45%
69 Riverside	47%	22.2	35%	12%	-0.23	42%	5%	-0.22	43%	3%
70 R. Cucamonga	43%	23.5	24%	18%	-0.17	27%	15%	-0.19	32%	10%
71 Ontario	84%	25.1	30%	54%	-0.17	42%	42%	-0.14	38%	45%
72 San Bernandino	27%	22.2	34%	-7%	-0.25	45%	-17%	-0.22	44%	-16%
Ave. Difference				**23%**			**22%**			**18%**

separate groups. One is a group of subcenters which has potential for growth due to their shorter travel time and wage premia, but has not grown as predicted. These centers have future growth potential, and are Fountain Valley and Garden Grove in Orange County, Ventura in Ventura County, and San Bernardino in Riverside County/San Bernardino County. The other group consists of subcenters in Los Angeles County. Even though they have smaller predicted growth due to their longer travel time and bigger wage premia, they have not reached the predicted level. These subcenters will decline further in the future. Los Angeles City, again, shows stable growth and almost achieved the growth level predicted by its travel time.

4.4.4. Findings

We found negative and significant correlation between growth of subcenter, and travel time and wage premia. This negative correlation means that subcenters with shorter travel time and smaller wage premia will grow rapidly. We also found that this correlation was much stronger than that with scale of subcenters. Thus, travel time and wage premia are more directly related with growth of subcenters than with scale of subcenters.

Through analysis of actual and predicted growth of subcenters, we learned that most of rapidly growing subcenters are located at Riverside County/San Bernardino County. These subcenters may increase their travel time and work premia in the future. However , San Bernardino, which did not reached the predicted level in these seven years will not experience serious congestion or soaring prices in near future. Therefore, this subcenter may keep growing its market.

5. Forecasting Office Submarket Growth

5.1. Vacancy Rate Forecasts

In Chapter 4, we observed that scale and growth of subcenters are closely related to travel time and wage rates of the corresponding subcenters. The larger subcenters have longer travel time and larger wage premia for their workers, shorter travel time and smaller wage premia cause faster growth of subcenters.

In this chapter, using equations estimated previously, we will forecast a future of the Los Angeles metropolitan office market: vacancy rates and rents of subcenters. Finally, we will find the best location for investments in the area.

1) Computing Absorption of Each Submarket

We use the following growth equation with coefficients estimated in the previous chapter. The equation for travel time was chosen, because it shows the best results among three equations. In order to calculate future absorption level for 6 years between 1994 and 2000, we use the most recent rents of 1994 (R_i94) instead of R_i90 and the most recent occupied stock level of 1994 (OC_i94). Thus, the equation become:

$$AB_i94\text{-}2000 \,/\, OC_i94 = 1.36522463 - 0.0661999\ T_i + 0.02879996\ R_i94$$

where $AB_i94\text{-}2000$ is the total net absorption of each subcenter for six years between 1994 and 2000, OC_i94 is the total occupied office stock of each subcenter in 1994 and R_i94 is the asking rent of each subcenter in 1994.

By substituting actual figures from the data into OC_i94 and R_i94, we can predict absorption for each submarket for the six years between 1994 and 2000.

2) Adjusting the Forecasted Absorption by Economic Effect

The previously calculated numbers, however, do not include any economic exogenous changes, but simply historic data. The total absorption between 1988 and 1994 was at a very low level as shown in Table 5.1. Since we used this data for estimating the equations, the predicted absorption between 1994 and 2000 was very low.

Table 5.1: Absorption of Each County: Historic and Forecasted (1000sf)

COUNTY	Historic		Predicted (1994-2000)	
	1982 - 1988 (6 years)	1988 - 1994 (6 years)	By Equation (6 years)	Torto Wheaton (6 years)
Los Angeles	31,281	14,608	-8,003	14,235
Orange	11,647	9,295	5,320	6,379
Ventura	1,460	603	1,752	510
Riverside/San Bernardino	3,103	3,664	2,999	3,476
Total	47,491	28,170	2,068	24,600

Particularly, Los Angeles County was predicted to have negative absorption of -8 million square feet. Thus, we use the six year market prediction data from Torto Wheaton Research, whose numbers reflect the future economy of the area, to adjust our forecasted absorption. Torto Wheaton Research issued predictions up to end of the year 2000 for each county of the Los Angeles metropolitan area. Employing those data, we adjusted our predicted absorption using the following method. We first set the following equation:

$$SAB_i = AB_i + \mu OC_i94$$

where SAB_i is adjusted absorption for each subcenter between 1995 and 2000, and μ is a scale to adjust our predicted absorption. μ is set the following way:

$$\mu = \frac{AB_{CO94-2000} - \sum AB_{COi}}{\sum OC_{COi}}$$

where $AB_{CO94\text{-}2000}$ is absorption for each county between 1994 and 2000 predicted by Torto Wheaton Research, $\sum AB_{COi}$ is the total absorption for each county between 1994 and 2000 predicted by our method, and $\sum OC_{COi}$ is the total of actually occupied stock for each county in 1994. Thus, we keep total absorption of each county exactly a same level as Torto Wheaton Research's number.

3) Calculating Vacancy Rate

In order to calculate vacancy rates of each year, we assume that rates are equally incremented each year up to 2000, and all else equal. Table 5.2 shows our forecasted vacancy rates in 2000 based on the adjusted absorption level. We observe quite high negative absorption levels in several markets. However, these figures were derived under the assumption of no new supply coming into the markets, so the absolute values shown on the table should not relied upon. Rather, the predicted vacancy rates are recommended to be used for comparison purposes in each county.

Table 5.2: Results of Vacancy Forecasts in the Year 2000

PUMA	OC1994 (1000sf)	OC2000 (1000sf)	AB94-00 (1000sf)	VAC1994 (%)	VAC2000 (%)	Chg_VAC (%)
Orange Co						
42 Santa Ana	5383	5674	291	21.90	17.67	-4.23
43 Laguna Beach	293	415	121	7.80	-30.35	-38.15
44 Laguna Hills	904	1235	331	17.60	-12.59	-30.19
45 San Juan	543	766	223	15.40	-19.30	-34.70
46 Fountain Valley	726	976	250	16.00	-12.91	-28.91
47 Garden Grove	399	523	125	19.00	-6.34	-25.34
48 Irvine	33050	38088	5038	15.50	2.62	-12.88
Sum (Average)	41298	47677	6379	16.17	-8.74	-24.91
Los Angeles Co						
52 Burbank	3065	4023	958	7.40	-21.55	-28.95
53 Glendale	4516	5881	1365	9.50	-17.86	-27.36
54 Monterey Park	1930	2314	384	9.60	-8.40	-18.00
58 El Monte	1930	2125	195	19.70	-29.32	-49.02
59 Pomona	491	549	57	29.80	21.63	-8.17
60 Carson	216	224	8	23.80	20.88	-2.92
61 Inglewood	477	441	-37	27.90	33.42	5.52
62 Beverly Hills	5462	5539	77	19.30	18.16	-1.14
63 Pasadena	4806	5087	281	21.10	16.48	-4.62
64 San Gabriel Valley	26627	32454	5827	18.40	0.54	-17.86
65 Los Angeles City	81958	86002	4045	21.20	17.31	-3.89
66 Long Beach	5582	6655	1073	23.90	9.27	-14.63
Sum (Average)	137059	151294	14235	19.30	5.05	-14.25
Ventura Co						
67 Ventura	4518	5028	510	15.50	5.96	-9.54
Sum (Average)	4518	5028	510	15.50	5.96	-9.54
Riverside/San Bernardino Co						
68 Moreno Valley	282	356	74	17.00	-4.64	-21.64
69 Riverside	4924	6628	1705	16.90	-11.87	-28.77
70 R. Cucamonga	1307	1601	294	26.30	9.72	-16.58
71 Ontario	978	1203	224	18.80	0.19	-18.61
72 San Bernandino	3594	4773	1180	24.60	-0.15	-24.75
Sum (Average)	11085	14561	3476	20.72	-1.35	-22.07

5.2. Rent Forecasts

In the commercial real estate markets, vacancy rates are believed to be one of the most important parameters to evaluate market conditions. People do not have much doubt about prevailing arguments that rental movements can largely be explained by vacancy rates. Based on this idea, we tested the following linear relationship in short run rental movements, using the original CB Commercial data for 43 submarkets in the Los Angeles metropolitan area:

$$R_{it} = \alpha + \beta V_{it-1} + \tau V_{t-1} + \omega R_{it-1}$$

Where R_{it} is the rent of each submarket at year t, V_{it-1} is the previous year's vacancy rate of each submarket, V_{t-1} is the vacancy rate of the metro area, and R_{it-1} is the previous year's rent of each submarket.

The results of estimates on Table 5.3 strongly support the argument for vacancy rates in real estate. All independent variables are very significantly correlated with R_{it}, with R^2 of 0.9. These results suggest that rents are very strongly related to the previous year's rent, though this is a foregone conclusion. The more interesting finding here is that rent of

Table 5.3: Result of Estimation:
$$\mathbf{R_{it} = \alpha + \beta V_{it-1} + \tau V_{t-1} + \omega R_{it-1}}$$

Regression Statistics			
Multiple R	0.9492468		
R Square	0.9010696		
Adjusted R Square	0.9000703		
Standard Error	1.6261222		
Observations	301		
Parameter Estimates			
Term	**Coefficients**	**Std Error**	**t Stat**
Intercept (α)	11.6183245	1.2740156	9.1194525
V_{it-1}	-0.0433299	0.0144983	-2.9886287
V_{t-1}	-0.4977241	0.0632447	-7.8698102
R_{it-1}	0.9137378	0.0191583	47.6942106

each submarket is over 10 times more influenced by the vacancy rate of the metropolitan area than by the vacancy rate of the submarket.

In order to compute rental indices, the estimated coefficients are first plugged into the equation:

$$R_{it} = 11.6183245 - 0.0433299\ V_{it-1} - 0.4977241\ V_{t-1} + 0.91373782\ R_{it-1}$$

For forecasting 1995 rents, we used the actual data of rents and vacancy rates in 1994. Thereafter, these calculated rents are used for the estimation of next year rents, as well as previously forecasted vacancy rates. Since only the vacancy rates in 2000 were predicted by the vacancy forecasts, we equally distributed the difference in vacancy rates in 1994 and predicted rates in 2000 across the six years 1994 through 2000. Completed rental indices for the period from 1994 to 2000 are shown on Table 5.4. Since we assume that there are no new completions coming into the markets, rents increase dramatically in all submarkets from 1994 to 2000 by 41.6% to 116%. Furthermore, the amount increasing each year does not vary significantly across subcenters. This is due to the fact that rents of submarkets are substantially more influenced by the metro vacancy rates than by their vacancy rates.

5.3. Findings

As we already discussed, our forecasts are based on the assumption that all else is held equal. Thus, each absolute number has little sense when viewed individually. However, these forecasts provide some comparative valuation of the future office markets of subcenters.

1) Vacancy Forecasts

As far as vacancy rates in 2000 are concerned, the three best performers are El Monte, Laguna Beach and San Juan. These are considerably small markets and two are located in Orange County. Looking at the larger subcenters, Burbank and Glendale, located in Los Angeles County, show pretty good results. The worst three performers are

Table 5.4: Forecasted Rent Indices 1994–2000

PUMA	1994	1995	1996	1997	1998	1999	2000	Chg%
Orange Co								
42 Santa Ana	15.21	15.13	15.98	17.67	20.13	23.30	27.11	78.2%
43 Laguna Beach	18.68	18.91	20.29	22.71	26.08	30.33	35.37	89.3%
44 Laguna Hills	17.56	17.47	18.48	20.52	23.48	27.30	31.89	81.6%
45 San Juan	18.32	18.26	19.33	21.46	24.53	28.48	33.23	81.4%
46 Fountain Valley	15.53	15.68	16.91	19.13	22.26	26.21	30.92	99.1%
47 Garden Grove	17.31	17.18	18.12	20.06	22.90	26.56	30.98	79.0%
48 Irvine	18.01	17.97	18.91	20.75	23.41	26.82	30.92	71.7%
Los Angeles Co								
52 Burbank	22.24	22.18	23.23	25.28	28.25	32.06	36.63	64.7%
53 Glendale	20.32	20.34	21.44	23.53	26.53	30.35	34.92	71.9%
54 Monterey Park	19.46	19.55	20.65	22.67	25.53	29.16	33.49	72.1%
58 El Monte	17.37	17.20	18.29	20.52	23.80	28.04	33.16	90.9%
59 Pomona	12.39	12.21	13.00	14.66	17.12	20.32	24.19	95.2%
60 Carson	15.22	15.06	15.82	17.42	19.79	22.87	26.59	74.7%
61 Inglewood	14.17	13.92	14.54	15.96	18.09	20.90	24.30	71.5%
62 Beverly Hills	22.18	21.61	21.99	23.23	25.26	28.01	31.41	41.6%
63 Pasadena	19.62	19.20	19.73	21.14	23.34	26.28	29.88	52.3%
64 San Gabriel Valley	18.40	18.20	19.03	20.81	23.44	26.87	31.02	68.6%
65 Los Angeles City	19.52	19.10	19.63	21.03	23.23	26.15	29.73	52.3%
66 Long Beach	18.77	18.30	18.86	20.37	22.73	25.89	29.77	58.6%
Ventura Co								
67 Ventura	15.64	15.80	16.91	18.87	21.62	25.09	29.22	86.8%
Riverside/San Bernardino Co								
68 Moreno Valley	13.29	13.59	14.91	17.15	20.25	24.12	28.70	116.0%
69 Riverside	14.25	14.47	15.77	18.05	21.23	25.22	29.97	110.3%
70 R. Cucamonga	12.91	12.84	13.78	15.65	18.36	21.85	26.04	101.7%
71 Ontario	16.64	16.57	17.53	19.43	22.19	25.73	29.98	80.2%
72 San Bernandino	13.43	13.39	14.42	16.42	19.32	23.03	27.49	104.7%

Inglewood, Beverly Hills and Carson. These three subcenters are all located at Los Angeles County. These are followed by Pasadena and Los Angeles City, also both in Los Angeles County. Among the counties, Orange County shows the best results.

2) Rent Forecasts

Winners and losers are clearly separated into the particular counties. All four subcenters which show above 100% rent increases over 6 years are located in Riverside County/San Bernardino County. These are Moreno Valley, Riverside, Rancho Cucamonga and San Bernardino. On the other hand, not surprisingly all losers are located in Los

Angeles County. They are Beverly Hills, Los Angeles City and Pasadena. Particularly, Beverly Hills shows up on both forecasts as a bad performer.

6. Conclusion

This paper has reserved the facts and causes of office decentralization in the Los Angeles metropolitan area. The long term trend of office movements from the central locations to the fringe submarkets was observed. As Los Angeles County decreased its share in the area's total employment over 28 years from 83% to 65%, the three other regions increased their share in the same period. Accordingly, these three counties extended their total share in area's office stock to 28.8% in 1994 from 14.2% in 1974, whereas Los Angeles County declined to 71.2% from 85.8%. In Los Angeles County, however, Los Angeles City kept a stable share of net absorption in the area, although most other subcenters in this county lost their share.

Average travel time of workers and estimated wage premia are found to vary significantly over subcenters. Also, we found a significant positive correlation between average travel times and wages across different work zones within the Los Angeles metropolitan area. As theory predicted, larger subcenters have longer travel times and higher wage premia; and conversely smaller travel times and lower wage premia cause faster growth of subcenters.

Based on these findings, estimated wage premia and average travel time for each subcenter from the 1990 Census data was used to forecast absorption, vacancy rates and rents. According to these forecasts, the losers are very much concentrated in Los Angeles County. In particular, Beverly Hills was ranked as the worst subcenter in terms of both vacancy rates and rents. Whereas winners in terms of vacancy rates are mainly in Orange County, and all winners in terms of rents are in Riverside County/San Bernardino County.

6.1. Score Matrix

We evaluated each subcenter based on several findings in this paper on Table 6.1. In each criterion, the subcenter with the best was given 10 points and one with the worst was given 0. Others were given points relative to these two extremes between 0 and 10. For the criteria, 'Scale' and 'Growth', points are the averages of the points for travel time and the points for wage premia. Total points from the six criteria were finally adjusted into the 100 scale.

6.2. Results from the Score Matrix

The worst performing subcenters in this study are Beverly Hills with 14.5 points, Los Angeles City with 29.0 points, and Pasadena with 30.4 points. All three are located in Los Angeles County. On the other hand, the best performing subcenter is San Bernardino in San Bernardino County with 83.6 points; Riverside in Riverside County and Garden Grove in Orange County are the second and third best with 81.4 points and 71.1 points respectively.

As far as acquired points are concerned, the future for the office property market in the Los Angeles central locations does not appeared to be good. The results of the previous chapter tell us that the trend of decentralization will continue in the future. However, it is also true that the downtown holds a stable share of the area's absorption over the years and its efficient highway system keeps commuting time and wages levels lower relative to its size of stock.

Table 6.1: Score Matrix

PUMA	Time	Wages	Scale	Growth	Vac	Rent	Points
Orange Co							
42 Santa Ana	4.8	3.0	3.5	5.0	1.8	4.9	38.4
43 Laguna Beach	8.7	7.4	7.5	0.7	8.0	6.4	64.5
44 Laguna Hills	8.5	3.2	4.9	5.8	6.5	5.4	57.3
45 San Juan	8.8	4.3	5.5	5.6	7.4	5.3	61.6
46 Fountain Valley	9.0	3.9	5.3	8.3	6.3	7.7	67.6
47 Garden Grove	7.8	7.1	7.1	9.9	5.7	5.0	71.1
48 Irvine	5.1	2.9	5.1	4.6	3.4	4.0	41.8
Average							57.5
Los Angeles Co							
52 Burbank	4.4	0.4	1.7	4.5	6.3	3.1	34.1
53 Glendale	5.1	2.2	3.1	4.7	6.0	4.1	42.0
54 Monterey Park	3.9	4.7	4.1	3.7	4.3	4.1	41.4
58 El Monte	3.4	5.8	4.6	6.9	10.0	6.6	62.2
59 Pomona	5.7	5.5	5.4	7.2	2.5	7.2	55.9
60 Carson	3.3	2.9	2.9	8.3	1.5	4.4	38.9
61 Inglewood	2.1	3.8	3.2	8.2	0.0	4.0	35.5
62 Beverly Hills	0.0	0.0	0.1	7.4	1.2	0.0	14.5
63 Pasadena	1.8	3.7	3.1	6.5	1.9	1.4	30.4
64 San Gabriel Valley	4.7	3.3	4.9	5.0	4.3	3.6	42.9
65 Los Angeles City	1.7	0.9	5.5	6.1	1.7	1.4	29.0
66 Long Beach	4.1	2.5	2.9	6.8	3.7	2.3	37.0
Average							38.6
Ventura Co							
67 Ventura	10.0	6.4	7.7	7.3	2.8	6.1	67.0
Average							67.0
Riverside/San Bernardino Co							
68 Moreno Valley	8.5	4.7	5.9	1.0	5.0	10.0	58.5
69 Riverside	9.3	9.5	9.5	5.0	6.3	9.2	81.4
70 R. Cucamonga	8.1	7.8	7.8	4.2	4.1	8.1	66.9
71 Ontario	6.6	6.9	6.5	1.1	4.4	5.2	51.2
72 San Bernandino	9.4	10.0	9.8	6.9	5.5	8.5	83.6
Average							68.3

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